How (not) to motivate online workers: Two controlled field experiments on leadership in the gig economy

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Abstract

An increasing number of workers participate in online labor markets. In contrast to traditional employment relationships within firms, the interaction between online workers and their employers are short and impersonal, which makes motivating online workers more challenging. We present results from two large-scale controlled field experiments on Amazon Mechanical Turk investigating the effects of monetary rewards and soft leadership techniques on output quantity and quality. In the first study, we investigate the effects of monetary rewards and simple upfront messages (praise or reference points). Monetary rewards increase quantity significantly. Sending simple messages, however, can have a significantly negative effect on quantity. The second study concentrates on the effects of communication based on charismatic leadership techniques. Charismatic communication techniques can also backfire if only a subset of them is used, whereas using a broad set including quantitative goals increases output quantity significantly. Neither intervention had a significant effect on the quality of work.

Keywords: Online Labor Market, Monetary rewards, Motivation, Charismatic Leadership, Gig Economy

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1 Introduction

In companies, leaders motivate the workforce to act in the interest of the organization and work towards common goals (Bass, 1985, 1990; Burns, 1978; House, 1996; Judge and Piccolo, 2004). Good leaders enable teams and individuals to function well, which leads to improved motivation, and results in greater revenue for the organization. In traditional employment relationships, workers are motivated by a well-balanced combination of contract-based reward systems and soft leadership techniques that rely on personal interaction and communication between leaders and followers (Zehnder et al., 2017). Leaders can for example provide a vision, define meaning and goals, praise performance, or employ rhetorical techniques. One prominent example for soft leadership techniques is charismatic leadership that is defined as "values-based, symbolic, and emotion-laden signaling" (Antonakis et al., 2016).

Leadership has been largely researched within traditional employment relationships, which feature long-term employment and regular personal interactions. Nowadays, however, we see new forms of labor emerging. A rising share of individuals works in so-called online labor markets. The International Labour Organization (ILO) regards the emergence of online digital labor platforms as the major transformation of work life in the last decade (ILO, 2018). Up to now, we lack a systematic understanding on whether and how well-established leadership techniques can be used to motivate online workers. Monetary rewards are straightforward to implement in online labor markets. Employing soft leadership techniques that traditionally utilize recurring face-to-face communication seems to be a much bigger challenge for several reasons. First, online workers often lack information about their tasks' contribution to the employers' goals because they work under spot contracts for many different employers. Second, online workers usually work from home and do not have any personal contact with employers or coworkers. Third, communication is typically one-way and in a written format. Employers send short digital messages that lack non-verbal elements such as visual or auditory clues, which are main carriers of emotional communication (Purvanova and Bono, 2009). Overall, leaders in the online world have a greatly reduced set of techniques at their disposal compared to leaders in traditional employment relationships.

However, applying soft leadership techniques when communicating with workers may be particularly valuable in online labor markets. Online workers often perform simple and boring tasks and are not aware of the value of their work. In such a work environment, it may be essential to provide workers with vision, meaning, and a clear purpose of work. Monetary rewards are easy to implement, but pure contractual arrangements are problematic due to the inherent incompleteness of contracts. Typically, tasks have different dimensions of which not all are easily measurable, such as quantity and quality of work. Rewarding workers for the easily measurable dimensions may distract workers' attention from the less easily measurable, but also important, dimensions (Holmström and Milgrom, 1991). Using soft leadership techniques could therefore be both more effective and less costly than granting monetary rewards.

We present two controlled field experiments addressing the question on whether and how monetary rewards and soft leadership techniques can be used to motivate workers in online labor markets to increase their performance (measured as output quantity and quality). We focus on soft leadership techniques that can be applied in upfront, written communication because—as mentioned above—other communication channels are typically absent in online settings. More specifically, we investigate performance effects of (i) monetary rewards, (ii) simple upfront messages that either praise workers or provide reference points, and (iii) more elaborate upfront messages that utilize charismatic leadership techniques.

In our first study, we investigate how performance is affected by monetary rewards and simple upfront messages expressing praise or communicating output-related reference points. We hypothesize that our upfront messages can motivate workers by changing their beliefs or preferences. That is, we interpret our upfront messages as two instances of transformational leadership techniques in the notion of Zehnder et al. (2017).[1] We also study the interaction between monetary rewards and our upfront messages. For employers who seek the optimal combination of all available motivational devices, it is important to understand whether soft leadership techniques make monetary rewards more or less effective.

Our first study reveals surprising performance effects of upfront messages, calling for a systematic analysis of soft leadership techniques using upfront communication. In our second study, we therefore apply the concept of charismatic leadership to an online setting. Previous research has shown that charismatic techniques work in on-site settings (Antonakis et al., 2011, 2019; Meslec et al., 2020) and provide a solid basis for testing and reliably coding different aspects of charismatic leadership communication (Antonakis et al., 2016). We investigate whether charismatic leadership tactics (CLTs) can be effective in online labor markets as well, where non-verbal CLTs such as body language and tone of voice are absent. We also explore how different sets of verbal CLTs affect performance. In particular, we disentangle the effects of quantitative goals and goal-related tactics from other CLTs. We test goals separately because goals are often used in isolation and are considered to be effective motivational instruments in the fields of psychology, management (e.g., Locke and Latham, 1984, 2002), and economics (e.g., Goerg and Kube, 2012).

Our studies help to extend leadership research to a setting where there is no organizational context, no repeated interaction between employer and worker, and only one-way written communication. Our research design allows us to establish causal relationships between the implementation of leadership techniques and workers' performance in an online labor market. Our results inform the large and steadily growing number of online employers who seek productive workers and contribute to recent research on work incentives or participation decisions in online labor markets (e.g., Chandler and Kapelner, 2013; DellaVigna and Pope, 2018; de Quidt, 2018; Farrell et al., 2017; List and Momeni, 2017; Butschek et al.,

[1] Seminal works on transformational leadership include Burns (1978), Bass (1985), and Bass (1990).

2019).

The remainder of the paper is organized as follows. In the next section, we provide information on the labor market platform that we have used for our studies. In Sections 3 and 4, we present hypotheses, design, and results of study 1 and study 2, respectively. Section 5 provides a general discussion of the results. Finally, Section 6 concludes.

2 Online labor market platform

Nowadays, millions of online workers sell everything from complex consulting services to simple production and routine jobs through platforms such as Elance-oDesk, Eden McCallum, or Amazon Mechanical Turk. Over one-third of U.S. workers participate in the so-called gig economy, either through their primary or secondary jobs (Gallup, 2018). The world-wide annual growth of the so-called 'gig economy' has been estimated to be 14% (Kässi and Lehdonvirta, 2018). Advancements in information and communication technologies have dramatically lowered the transaction costs of using online markets, and this trend can be expected to continue, suggesting that both firms and workers will use online labor markets even more in the future (Coase, 1937; Munger, 2015). Online labor platforms have not only disrupted existing business models, but also fundamentally changed employment relationships.

To study behavior in an online labor market, we chose to conduct our studies on Amazon Mechanical Turk (MTurk), one of the most prominent and widely used platforms that currently exist (Peer et al., 2017). MTurk offers firms the opportunity to outsource small, manual tasks to a large number of online workers. Potential employers, called "requesters," post job offers on the MTurk platform and can specify a set of criteria that workers have to meet in order to be allowed to work on the task. These screening options can either be related to the reputation of the worker, such as the total number of tasks the worker has previously completed, the share of tasks that the worker previously got approved (the so-called approval rate), or to specific demographics of the worker, such as location, age, or gender.

Workers who are registered on the MTurk platform can browse among available tasks that fit their criteria or search for job offerings posted by particular employers or according to keywords used in the task description. This description typically contains information about the offered payment as well as the task duration. Workers who accept a work task then have to complete the task within a specified time interval set by the employer. After task completion, the employer reviews the submitted task and can approve and pay the worker or reject the work. In the case of a rejection, the approval rate of the worker drops, leading to a loss of the worker's future potential to find suitable job offers. An approval rate of 98% is often deemed critical in this regard among workers and employers.

There is typically no communication between worker and employer besides some basic information on the work task that employers post on MTurk and more specific instructions about the task that employers provide once the workers has accepted the task. If needed, workers can contact the employer via email and it is up to the employer to answer the requests or not.

Workers receive their payment through the platform from the employer. The employer freely decides on the amount of payment he or she is willing to offer. This payment will be announced in the job description posted on MTurk. If the employer accepts the work, the worker's account will be credited with the respective payment. Employers can offer a fixed payment for a task and also assign bonus payments to workers to reward exceptional performance. In addition, employers are also able to assign a qualification to workers and offer future work only to workers with this qualification level. Other mechanisms for rewarding and motivating workers are not part of the platform.

3 Study 1

3.1 Aim and hypotheses

In study 1, we investigate how work performance is affected by monetary rewards in the form of piece rates and non-monetary motivational techniques in the form of short upfront messages. We use a text transcription task, which is a typical task on MTurk that allows us to measure both quantity and quality of output. We can thus study potentially diverging effects of our interventions on the two different performance dimensions (see subsection 3.2 for a detailed description).

All workers obtain a fixed wage for participating in the study. In addition, they receive either no piece rate, a low piece rate, or a high piece rate. We use two different piece rates to investigate the relationship between piece rates and performance, and in particular how this relationship depends on the height of the piece rate. Workers further receive either no upfront motivational message, an upfront message that praises workers' past performance based on their approval rates, or an upfront message that establishes a reference point regarding the quantity of output. Messages are displayed after the task description and before the work phase because this form of communication from employers to workers is most straightforward on the platform.

Paying workers more for achieving a higher output should motivate them to worker harder. However, if workers want to increase their payment under a piece rate, they will have to work faster, which may result in a lower output quality. Moreover, workers may intentionally shirk on quality to obtain higher payments. Using piece rates can lead to a multitasking problem (Holmström and Milgrom, 1991).

We first concentrate on the effects of monetary rewards on workers' performance irrespective of any upfront messages and thus make the following predictions:

Hypothesis 1a. Output quantity will be higher in situations where workers receive a piece rate in addition to the fixed wage compared to situations without *a piece rate.*

Hypothesis 1b. Output quality will be lower in situations where workers receive a piece rate in addition to the fixed wage compared to situations without a piece rate.

Hypothesis 1c. Output quantity will be higher in situations where workers receive a high piece rate in addition to the fixed wage compared to situations where they receive a low piece rate in addition to the fixed wage.

By praising workers, the employer expresses recognition and appreciation for the workers. Workers may feel the need to reciprocate the friendly gesture by doing a good job (Falk and Fischbacher, 2006). Moreover, by referring to high approval rates, employers remind workers of their past good performance and workers might feel the need to live up to that implicit expectation of good work. We therefore predict that praise enhances performance in both dimensions, quality and quantity of delivered work.

Hypothesis 2a. Providing praise will increase output quantity compared to situations without an upfront message.

Hypothesis 2b. Providing praise will increase output quality compared to situations without an upfront message.

When we provide a reference point, we ask workers to submit 25 fragments. We aimed to establish a reference point that is challenging but at the same time achievable for the average worker. We have chosen this output quantity based on data of the treatments without monetary rewards and no message intervention where workers managed to type 22.28 fragments on average. Achieving 25 fragments translates into an average increase in output compared to the before mentioned treatments of 12% and belonging to the 39% of best performers.[2] We hypothesize that providing this reference point increases the output quantity as workers want to reach the reference point of 25 fragments compared to treatments without a reference point. In economic terms, providing a reference point may trigger reference-dependent utility, which means that, ceteris paribus, workers experience a higher utility when they reach the reference point compared to when they produce less than the reference point (Corgnet et al., 2015, 2018). However, as argued above, working faster may lead to lower quality of work. Thus, quality should decrease when a reference point is provided. Overall, we thus suggest that:

Hypothesis 3a. Providing an output-related reference point will increase output quantity compared to situations without an upfront message.

Hypothesis 3b. Providing an output-related reference point will decrease output quality compared to situations without an upfront message.

[2] Experimental evidence on the effective provision of reference points is still scarce. Corgnet et al. (2015) report that, in their experiment, an average worker exceeded the baseline output by 11% in the goal-setting treatments.

Providing praise or reference points aims at changing workers' behavior by exploiting their social or reference-dependent preferences, respectively. Hypotheses 2a, 2b, 3a, and 3b therefore address the impact of instances of transformational leadership techniques on workers' performance.

We are also interested in the interaction effects between monetary rewards and upfront messages. Psychological theories of motivation predict that monetary rewards alone can crowd out intrinsic motivation and thereby weaken performance (e.g., Deci, 1971). However, recent behavioral economic theories (e.g., Bénabou and Tirole, 2003; Ellingsen and Johannesson, 2008) imply that crowding out effects may be reduced or eliminated if the principal can resolve informational asymmetries. For example, communication by a leader can help clarify the nature of the task or reveal more information about the personality and intentions of the leader. Indeed, Kvaløy et al. (2015) find in a field experiment that motivational talk enhances the effectiveness of monetary rewards. Following this line of argumentation, we expect that upfront text messages and monetary rewards are complements also for the online workers we study. We thus propose the following two hypotheses on the interaction between monetary rewards and transformational leadership techniques.

Hypothesis 4. Combining praise with monetary rewards will increase output quantity compared to situations where only one of the two instruments is used.

Hypothesis 5. Combining an output-related reference point with monetary rewards will increase output quantity compared to situations where only one of the two instruments is used.

3.2 Design

3.2.1 Work task

We asked workers to type text from a series of fragments taken from an ancient Latin text for a total duration of 10 minutes. The fragments had an average length of about 50 characters and were shown as a picture on the screen, such that workers were prevented from simply copying and pasting the text. Workers only saw a single fragment at a time and had to submit their transcription in order to receive a new fragment on their screen. The typesetting of the letters for all fragments was historic so that some letters were harder to read than others. The task therefore requires effort, attention, and diligence. An example fragment is given in Figure 1.

[Figure 1 about here]

3.2.2 Treatments

We employed three different compensation schemes. Workers received either only a fixed wage of \$2, or, on top of the fixed wage, a low piece rate of \$0.01 or a high piece rate of \$0.05 per submitted fragment. We informed workers about the piece rate in the following way: *"In addition, you will receive a bonus of $0.01 ($0.05) for each completed fragment. The compensation will be sent to you within two days after the completion of this HIT."* A piece rate of $0.05 leads to a considerable potential earnings increase compared to a piece rate of only $0.01. For example, a worker who submits 25 fragments yields a $1 higher payment under the high piece rate than under the low piece rate.

To investigate whether written upfront messages have an impact on performance, workers either receive no message, a praise message, or a reference point message. Workers who received a message saw a simple screen before starting to work on the task. The praise message reads as follows: *"Before you start, we want to emphasize how happy we are that you've decided to work for us. You've proven to be a successful and diligent worker on MTurk with an impressive approval rate!"* The reference point message is: *"Efficient work is important. Please try to submit at least 25 fragments"*. We included the first sentence in the message to provide a mild justification for asking for a specific amount of output and to make the two messages more similar in length. Workers could leave the message screen at any time by clicking on a button to proceed to the work task. The complete instructions provided to the workers can be found in Section 6.2 of the Appendix.

For the purpose of comparison, we combine the three message settings with each compensation scheme, respectively. The resulting 3x3 treatment design is summarized in Table 1.[3]

[Table 1 about here]

3.2.3 Sample and procedures

For our study 1, we invited a total of 2700 workers from MTurk. Workers responded to a job posting offering a ten-minute work task for a $2 payment that had to be completed within one hour. Our selection criteria for workers stipulated that subjects on MTurk needed to have a total number of 500 previously approved tasks and a task approval rate of 98%. In addition, only workers who indicated their location as the United States were eligible for participation. For the design and conduct of the study, we closely followed guidelines mentioned in a series of articles that discuss the use of MTurk in behavioral research (Paolacci et al., 2010; Horton et al., 2011; Berinsky et al., 2012; Mason and Suri, 2012; Crump et al., 2013; Paolacci and Chandler, 2014). Measures were taken for excluding duplicate workers, workers who participated in earlier related experiments, and checking for workers who attempt to self-select into treatment.[4]

[3] As a robustness check, we conducted treatments where workers receive no message or the praise message with no, low, and high piece rates where we told workers that their work would be approved automatically. We thus cut off any potential concerns that workers may have regarding the impact of their performance in our task on their approval rates. As the results do not differ compared to treatments where we did not explicitly mention automatic approval, we pooled the data.

[4] We find that 30 workers in our sample restart their work task, which however did not result in any selection effect.

Workers who accepted the job offer followed a link to an external website (Qualtrics) that we used for data collection. After workers gave their consent to participate in the study and finished reading the task instructions, they started working on the task. The task stopped automatically after ten minutes. At the end, all workers answered a short survey and received a code for verification.[5]

[Table 2 about here]

The survey contained demographic questions as well as questions regarding the worker's familiarity with Latin and the device used to complete the task. Table 2 provides an overview of the background characteristics of subjects participating in study 1. Workers were, on average, 36 years old, possessed a two-year college degree, and were only vaguely familiar with Latin. About five percent used a mobile device to complete the task. The sample also contains an equal number of male and female workers. Importantly, we observe that the treatments are balanced with respect to all of these characteristics.[6]

Altogether, workers spent on average 13 minutes to complete the work task and the survey. Average payments made amounted to \$2.80, including the \$2 participation fee. All payments were made electronically. Participation fees were paid out soon after the study had been completed. Payments based on performance were transferred within two days after the study was conducted.

3.3 Results

3.3.1 Quantity

We first address the question of whether changes in monetary rewards as well as upfront motivational messages affect output quantity, measured as the number of fragments submitted per worker. In a first step, we focus on differences between distributions of the number of fragments submitted. Figure 2 plots the inverse cumulative distribution function (ICDF) for the number of submitted fragments separated by the type of intervention. In particular, the upper panel of the figure presents the data from all treatments split by the type of monetary rewards provided. Thus, the No-piece-rate ICDF includes all treatments without monetary rewards no matter whether an upfront message was used or not. The Low-piece-rate ICDF shows data from all treatments with a low piece rate and the data used for the High-piece-rate ICDF contains all treatments where a high piece rate was offered. The figure allows us to initially study the impact of monetary rewards without taking into account potential interaction effects between monetary rewards and upfront messages.[7]

[5] Four workers accepted the invitation but never actually worked on the task and are therefore missing from the sample. In addition, the timer of the work task did not work properly for 16 workers who we exclude from the analysis. All excluded observations are unrelated to any treatment condition.

[6] We provide balance tests in Table S1.

[7] Figure S2 in the Appendix displays the means and standard deviations for the number of fragments submitted in each treatment.

[Figure 2 about here]

We see from the top panel in Figure 2 that the distribution of the number of submitted fragments including all treatments without a piece rate is stochastically dominated by the distribution of submitted fragments including data from all treatments with a low as well as a high piece rate (two-sided Kolmogorov-Smirnov test (KS), $p = 0.008$ and $p = 0.012$, respectively).[8] In particular, the vertical shift of the ICDF from treatments with a low and a high piece rate indicates that larger monetary rewards appear to increase output for low and high productivity workers evenly.

The bottom panel in Figure 2 plots the corresponding ICDF dividing the dataset by the use of upfront messages. In this panel, the No-message ICDF contains all treatments without an upfront message no matter whether a piece rate was paid or not. The Praise ICDF depicts the data from all treatments where an upfront praise message was shown, whereas the Reference-point ICDF shows all data from treatments including a reference point message. We find that the ICDF for the number of submitted fragments from subjects confronted with a praise message lies below the same function from the treatments where no message was sent (KS, $p = 0.054$). This observation suggests that praising workers prior to work tends to lower overall output. In contrast, the ICDF from the treatments including a reference point initially dominates the corresponding function from the treatments with no message, whereas it is dominated once the reference point is reached. The latter indicates that the explicit setting of a reference point prior to work increases output below the target output but it decreases output above it, harmonizing the exerted effort levels of workers. A comparison of variances supports this impression, showing that the variance in produced output is significantly lower in the treatments with a reference point than in the treatments with no message and treatments with praise messages (two-sided Levene's variance comparison test, $p < 0.001$ for both comparisons using data of the pooled treatments, respectively).

Next, we estimate the average treatment effect of increasing the piece rate per submitted fragment and the average effect of using praise or reference points on output. In addition, we estimate their interaction effects on output quantity. We use ordinary least squares (OLS) regressions with robust standard errors and employ a series of nested versions of the following regression specification to analyse our 3x3 factorial design:

$$\begin{aligned} Y_i = {} & \beta_0 + \beta_1 Low_i + \beta_2 High_i + \beta_3 Praise_i + \beta_4 ReferencePoint_i \\ & + \beta_5 Low_i \times Praise_i + \beta_6 High_i \times Praise_i \\ & + \beta_7 Low_i \times ReferencePoint_i + \beta_8 High_i \times ReferencePoint_i \\ & + \gamma X_i + \varepsilon_i, \end{aligned} \tag{1}$$

where Y captures the number of submitted fragments, Low, $High$, $Praise$, and $ReferencePoint$ are indicator variables for each monetary and non-monetary

[8] See Heathcote et al. (2010) for a discussion of stochastic dominance tests.

intervention, X_i is a vector of background characteristics for each worker i and ε_i is an error term. Note that the treatment effects are captured by a combination of indicator variables. For instance, in the saturated specification without controls, the coefficient for the indicator variable *Low* corresponds to the *Low piece rate + No message* treatment effect relative to the *No piece rate + No message* baseline. The *Low piece rate + Praise* treatment effect relative to baseline can be estimated by adding the coefficients *Low*, *Praise*, and the interaction between both denoted by *Low* × *Praise*, respectively.

Model I in Table 3 reports main effect estimates for increasing piece rates from zero to \$0.01 and \$0.05. Estimate results reveal an increase in average output of 1.40 fragments ($p < 0.001$) for a low piece rate and an increase in average output of 1.42 fragments ($p < 0.001$) for a high piece rate (support for Hypothesis 1a). These changes correspond to a relative increase in average output of about 6.3% when compared to using no piece rate payment. Furthermore, we fail to identify any difference in effects between the two piece rates (no support for Hypothesis 1c), suggesting that the minimum piece rate payment of one Cent increases worker output as much as a five times higher piece rate ($F(1, 2680) = 0.002$ $p = 0.963$).

Model I also lists main effect estimates for praising workers or communicating a reference point to them prior to work. We find that communicating reference points to workers insignificantly lowers workers' performance by 0.3 fragments ($p = 0.425$), whereas praising them significantly decreases output by 1.2 fragments ($p = 0.006$) relative to all situations with no upfront motivational message (no support for Hypotheses 2a and 3a).

Model II in Table 3 reports both main and interaction effects of all monetary and non-monetary interventions, which enables us to disentangle the effects of our different treatments. We do not find any significant interaction between praising workers prior to work and increased monetary rewards (no support for Hypothesis 4). In particular, whereas the low and high piece rates significantly increase the average number of submitted fragments ($p = 0.013$ and $p = 0.003$, respectively), the *Low piece rate* × *Praise* and *High piece rate* × *Praise* indicator variable estimates remain insignificant ($p = 0.802$ and $p = 0.884$, respectively).

In contrast, we identify from the *High piece rate* × *Reference point* indicator variable estimate that the expression of an explicit reference point curbs the positive effects that result from using a high monetary reward per submitted fragment ($p = 0.031$). Providing a reference point does not enhance the incentive effect as expected, but leads to harmonization of output compared to treatments without reference points (see ICDF discussion above). Furthermore, the linear combination of coefficients for the *Low piece rate + Low piece rate* × *Reference point + High piece rate + High piece rate* × *Reference point* is not statistically different from zero ($F(1, 2670) = 0.271, p = 0.603$), showing that, overall, increases in output through increased monetary rewards are offset by the explicit reference point (no support for Hypothesis 5).

Model III adds a set of worker background variables and shows the robustness of the results discussed so far. Background variables include gender, age, education, device used for the work task, and knowledge of Latin. From the set of background variables, we find that older workers submit, on average, fewer fragments whereas more educated workers and women show a higher work performance in the task. Knowledge of Latin is also predictive for higher worker output in the text transcription task, whereas mobile users, on average, submit five fragments fewer than non-mobile device users.

3.3.2 Quality

Next, we assess the quality of each submitted fragment by computing the Levenshtein edit distance to the correct fragment (Levenshtein, 1966). In particular, we calculate the minimum number of edit operations involving the insertion, deletion, or substitution of individual characters which are required to transform the submitted fragment into the correct fragment and apply a unit cost to each edit operation. We then normalize the processed edit distance by the upper bound of transforming the submitted fragment into the correct fragment, obtaining a ratio of dis-similarity of the two fragments that we interpret as the error rate. Workers could use the "?" character as a wildcard if they were unable to identify the actual character in the presented fragment. We see that workers on average only make use of 0.54 times the wildcard. Disregarding the use of the wildcard character when calculating the error rate does not change any result. We report means and standard deviations for the average error rate in Figure S3 in the Appendix.

Following the regression specification in Equation (1), Table 4 presents results from a series of nested random-effects panel regressions, where the dependent variable in each regression captures the error rate of a fragment the worker submitted.[9]

Model I reports main effect estimate results of changing the monetary and upfront-message interventions. We find that workers submit on average fragments that have an error rate of about 0.018, that is fragments which have a dis-similarity of about 1.8% with the correct fragment. Models II and III include interaction terms for both intervention dimensions with and without controls, respectively. Estimation results from these models fail to show any statistically significant interaction effect (no support for Hypotheses 1b, 2b and 3b). From the set of background variables, we find that female workers as well as more educated workers submit, on average, fragments with a smaller error rate, whereas mobile users deliver fragments that are more error prone.

[Table 4 about here]

On the basis of multitasking theory, a plausible concern in our work setting is that workers who type very fast and submit a large number of fragments deliver low-quality work because they neglect the quality dimension of their task.

[9] A Breusch-Pagan Lagrange multiplier test consistently rejects the null hypothesis of no significant difference across units for each specification. We therefore use a random-effects model.

Figure 3 plots for each worker the number of submitted fragments as a share of the total number of fragments a worker could submit (80 in total) against the average error rate for all submitted fragments by treatment. We consider this share as the completion rate a worker achieves.

[Figure 3 about here]

From the set of sample correlation coefficients that we obtain for each monetary and non-monetary treatment combination, we cannot identify a single significant positive linear relationship between workers' completion rate and the average error rate. Instead, we consistently find that workers who manage to submit a larger number of fragments also submit fragments that are characterized by a lower average error rate.[10]

We use a randomized instrumental variables approach (Sajons, 2020) in order to check whether the positive relationship between quality and quantity is merely associational or if an increase in average output indeed comes without the cost of fragment quality. In particular, we employ a two-stage least squares estimation (2SLS), where we treat quantity as the endogenous regressor to predict quality. As instruments for quantity, we use a linear combination of our treatment variables that offer variation in quantity independent of unobserved worker characteristics.

Results of the estimation are shown in Table 5, where we report both OLS and 2SLS estimation results (Antonakis et al., 2010). Model I shows OLS estimation results showing that an increase in a worker's share of fragments submitted is associated with a significantly lower average error rate ($p < 0.001$). In particular, the size of the estimate reveals that a one percentage point increase in a worker's completion rate relates to a decrease in the average error rate by 0.036 percentage points.

Models II and III report first and second stage estimation results for the 2SLS estimation. First stage results show the positive effect of both low and high piece rates, the negative effect of praise on worker output and the negative interaction of reference points with higher monetary rewards that were previously shown in Section 3.3.1. The partial F statistic exceeds critical values for testing weak instruments (Stock and Yogo, 2005) and shows that our set of instruments is sufficiently correlated with the suspected endogenous regressor ($F(8, 2680) = 30.87, p < 0.001$). Moreover, a Sargan-Hansen test of overidentifying restrictions is not significant ($\chi^2(7) = 8.25, p = 0.311$), giving support to the validity of our instruments.

The estimate results from the second stage reveal a negative albeit statistically insignificant relationship between the completion rate and average error rate corresponding to about half the size in magnitude as the OLS estimate. In addition, the Wu-Hausman ($F(1, 2672) = 0.204, p = 0.652$) and Durbin scores

[10] Table S3 in the Appendix shows regression results for regressing the averaged error rates per worker on the number of submitted fragments per worker. We allow for intercepts and slope parameters to vary separately as well as in combination. We identify no significant differences in slope or intercept parameters across treatments.

($\chi^2 = 0.024, p = 0.651$) are statistically insignificant, meaning that we fail to reject the null hypothesis that our OLS estimation results are consistent. Neither the OLS nor the 2SLS estimation can identify any statistically significant positive relationship between a worker's completion rate and the average error rate of the submitted fragments. We therefore conclude that changes in quantity as a result of our interventions do not come at the expense of lower average fragment quality in our first study.

3.3.3 Supplementary analysis

A possible explanation for the absence of a negative quantity-quality trade-off under monetary rewards is that workers were concerned about not receiving their piece rate payment if the delivered quality was too low and therefore, in response, typed more carefully than they would in the absence of such concerns. To address this issue, we employed additional clarification treatments where we explicitly informed workers that we would not check the quality of their submitted fragments. We implemented a special emphasis on the security of the piece rate payment regardless of whether the fragment was correct or not by stating to workers that *"In order to pay the bonus in due time, we pay it for submitted fragments without controlling for typing errors. Once you have completed the HIT, you will be approved automatically, which means that your performance will not affect your approval rate"*. In the clarification treatments, there was no need for workers to work diligently on the task in order to avoid being rejected and not receive the piece rate.

Using this clarification, we employed four additional treatments on a sample of 400 workers, including two treatments with a low and high piece rate payment scheme without any upfront message, and two treatments with the low and high piece rate payment scheme in combination with praise for prior work.[11] If the concerns about receiving work payment affected how workers in the original treatments evaluate the multitasking problem, we would expect to find a change in how workers trade-off quality for quantity when we signal that we do not control for mistakes.

[Figure 4 about here]

Figure 4 plots completion rates of workers against the average error rate for all submitted fragments by treatment for the additional sample. With the additional clarification regarding the absence of quality control, we still find no evidence that workers who submit a larger number of fragments also submit fragments of lower quality. Specifically, across all new clarification treatments, we estimate a sample correlation of $r = -.14$, ($p = 0.006$) between the number of submitted fragments and the average error rate. Furthermore, estimate results from OLS and 2SLS regressions which we present in Table S8 reveal that we cannot identify

[11] Two workers accepted the invitation but never actually worked on the task. In addition, two other workers had to be excluded after data collection because their timer did not function properly.

any significant negative trade-off between quantity and quality in our additional sample.

This result suggests that the absence of a negative quality-quantity trade-off in our original setting is not driven by asymmetric information concerning the implications of low quality work.[12]

3.4 Discussion

For simple work tasks where output quantity can be easily measured, several empirical studies have shown that adding piece rates to a fixed wage leads to higher output than paying only a fixed wage (e.g., DellaVigna and Pope, 2018; Antonakis et al., 2019; Meslec et al., 2020). For our task, paying a piece rate on top of the fixed wage increases output quantity compared to paying the fixed wage only. Our Study 1 also shows that the introduction of a very small additional piece rate works surprisingly well in the context we consider, whereas the marginal effect of increasing the level of monetary rewards is close to zero. This result contrasts with Gneezy and Rustichini's (2000)"Pay enough or don't pay at all" result, and is more in line with DellaVigna and Pope (2018) and Pokorny (2008), who find a strong effect of introducing an additional small piece rate, but, respectively, a low or even negative effect of increasing this additional piece rate.

Contrary to our Hypothesis 1b derived from multitasking theory, we find neither negative effects of the additional piece rate on the quality of work, nor more generally a significant negative correlation between quantity and quality of output, not even if the employer points out that work quality will neither affect payments nor approval rates.[13] Our results may thus indicate that online workers put some pride in doing a decent job, and are not driven by monetary or reputational incentives alone. Our results are in contrast to the results of two recent empirical papers that study worker behavior in traditional employment relationships and argue that the absence of multitasking problems under piece rates is due to reputational concerns. Hong et al. (2018) present a field study on Chinese factory workers that is in strong support of the multitasking theory. Workers who work under a fixed wage scheme react to a bonus treatment manipulation where the bonus is paid on top of the fixed wage. Both the produced quantity and the defect rate increased significantly for these workers. The authors argue that the key distinction of their setting relative to many others (that are not in line with the multitasking theory) is that quality is not only unrewarded but also

[12] In Table S4 and Table S5 in the Appendix, we provide regressions of quality on quantity, estimating slopes and intercept parameters for each additional treatment as well as parameters comparing the overall quantity quality trade-off with and without the additional clarification statement, respectively. We find no difference in the overall trade-off. In addition, we also present regressions of quantity and quality on a set of treatment variables in Table S6 and Table S7. We find no effect of the clarification statement on quantity or quality.

[13] We observe a negative correlation between quantity and quality in the clarification treatment "High piece rate + No Message + Clarification" but the correlation is not significant with p=0.915

truly unobservable by the employer, which is crucial to fully eliminate reputational concerns of workers. In a similar spirit, Al-Ubaydli et al. (2015) propose that workers' uncertainty about the employer's monitoring technology can even lead to higher quality under piece rates than under fixed wages.[14]

Sending a simple message that praises workers for their past performance before the work phase inhibits or even decreases workers' output in our study. This result is puzzling at first sight, but it may show that non-monetary motivational interventions can also have negative performance effects. However, the reduction in output could also be due to the interruption before the working stage itself and not due to the content of the message. If the drop in output is simply due to the interruption itself and not the content of the message, we would expect workers who receive a reference point message to also react negatively to the message because they spend a substantial amount of time reading the message as well.[15] However, we find no indication of a negative effect of our reference point message. Hence, we do not believe that the negative effect of praise on output quantity is driven by interrupting workers per se but by the content of the message.

Psychologists have studied praise as a social reinforcer and found that praising people can be ineffective or even dysfunctional (Delin and Baumeister, 1994). Baumeister et al. (1990) propose three mechanisms that can explain a negative impact of praise on output quantity. First, praising may cause people to feel that they no longer need to try hard, leading them to reduce subsequent effort. Second, praise may convey an implicit demand for continued high performance, leading to choking under pressure. Third, receiving praise makes people self-conscious, which impairs their performance. One or a combination of these mechanisms could be at work in our setting.

Our short and simple reference point message might not have been strong enough to trigger reference-dependent preferences and might have been perceived as a suggestion rather than a formal request to achieve this reference point. Our reference point resembles an externally assigned goal. Psychologists assert that assigned goals can be effective, but more so if the goal is ambitious and the assigning person explains the goal and expresses confidence that the goal can be achieved (see, e.g., Locke and Latham (2002) for an overview of the literature). Our simple message did not carry any such information. Thus, the treatment manipulation might have been too subtle to trigger higher performance. However, our data also revealed that the variance in the treatments with reference points is lower than in the treatments using praise or no upfront message, suggesting that workers have to some extent reacted to our intervention. The effects for high and low performing workers might have cancelled each other out. In addition,

[14] In contrast to our study, Al-Ubaydli et al. (2015) lower the fixed part of the worker's wage in the piece rate treatment compared to the flat wage compensation.

[15] Workers who receive a message are presented with a screen displaying the text message prior to work. Figure S1 in the Appendix shows that workers spend on average approximately 6 and 16 seconds reading the reference point message and praise message, respectively. Note that the reference point message is substantially shorter than the praise message.

the interaction effects with monetary rewards indicate that the positive effect of paying a piece rate on average output is likely to be offset by the introduction of a reference point. An intervention that carefully incorporates the recommendations of the goal setting literature might enhance average output, for instance by triggering higher output from low performers or diminishing the output decline of high performers relative to a less sophisticated goal intervention.

Overall, the negative effect of our praise intervention and the ineffectiveness of our reference point intervention calls for further analysis to clarify whether other and stronger forms of non-monetary interventions will also backfire in an online setting. We therefore conducted a second study where we address the points raised above.

4 Study 2

4.1 Aim and hypotheses

In study 2, we focus on non-monetary interventions based on charismatic leadership communication techniques. In particular, we investigate whether and how communication tactics used by charismatic leaders affect the performance of online workers, building on the concept of charismatic leadership as defined by Antonakis et al. (2011, 2016, 2019). Antonakis et al. (2016) define charismatic leadership as "values-based, symbolic, and emotion-laden signaling", which provides us with a suitable definition and operationalization of communication tools to develop an experimental design. Charismatic leaders use communication tactics, which can be organized in three major categories that can be reliably coded. The first category is "frame and vision", by which the leader tries to draw attention to the key issues of the job. The second category is "substance", which is used to justify the mission and announce strategic goals. "Frame and vision" can be provided by (i) metaphors, (ii) rhetorical questions, (iii) stories and anecdotes, (vi) contrasts, and (v) three-part lists. "Substance" can be induced by (vi) expressing moral conviction, (vii) expressing sentiments of the collective, (viii) setting high and ambitious goals, and (ix) creating the confidence that workers will be able to reach these goals. The two categories "frame and vision" and "substance" rely on verbal communication tactics, whereas the third category "delivery" is triggered by non-verbal tactics. By the use of voice, body gestures, and facial expressions the leader can demonstrate passion and confidence. As we want to study the effects of written messages in online labor markets, we do not implement the third category and thus focus on the first two.

Similar to Study 1, we employed a transcription task to measure both quality and quantity of the submitted work. Our main research question is if verbal tactics providing "frame and vision" as well as "substance" in a purely written form will be sufficient to increase output. In addition, we are interested in disentangling the effects of goal setting from other verbal CLTs, as simple quantitative goals are often used in isolation in practice and also have been studied in isolation before.

We conduct four treatments, named *Neutral*, *Goal*, *Charisma without goal* and *Full charisma*, that differ in the CLTs employed. In the *Neutral* treatment, the task is explained as neutrally as possible. The *Goal* treatment sets a specific quantitative goal utilizing the verbal CLTs (viii) and (ix). By contrast, *Charisma without goal* makes use of the remaining CLTs (only contrasts are not used) without setting a quantitative goal. Finally, *Full charisma* combines all CLTs used in the former two treatments. Thus, *Charisma without goal* features fewer elements triggering "substance" in comparison to the *Full charisma* intervention. The *Goal* treatment, in contrast, focuses only on a subset of CLTs related to the "substance" category.

For the derivation of our hypotheses, we build on the theoretical economic framework proposed by Antonakis et al. (2019). They assume that workers receive positive intrinsic utility from working on their task, and that the absolute and the marginal intrinsic utility from working increases in the perceived charisma of the leader, without addressing the specific psychological mechanism through which charisma impacts utility. Accordingly, if workers perceive the leader as more charismatic, they will work harder. Based on this framework and assuming that perceived charisma is at least weakly increasing in the number of CLTs employed, we expect that both quantity and quality of work increase in the *Full charisma* treatment relative to the *Neutral* treatment.[16] It is, however, unclear if the use of only subsets of verbal CLTs can trigger higher performance. In particular, in our setting, we cut off important non-verbal channels that a leader can typically use. It may be that subsets of CLTs are too weak to increase performance, but it is also possible that they are effective. We therefore expect to find either higher performance or no difference in performances when comparing the *Charisma without goal* with the *Neutral* treatment. The *Goal* treatment also employs only a subset of CLTs. Nevertheless, we expect these CLTs to increase performance relative to the *Neutral* treatment because research in psychology (e.g., Locke and Latham, 2002) and economics (e.g., Corgnet et al., 2018) asserts that assigning goals increases performance. This line of arguments leads to the following six hypotheses.

Hypothesis 1a. Output quantity will increase in the Full charisma treatment compared to the Neutral treatment.

Hypothesis 1b. Output quality will increase in the Full charisma treatment compared to the Neutral treatment.

Hypothesis 2a. Output quantity will increase in the Goal treatment compared to the Neutral treatment.

Hypothesis 2b. Output quality will increase in the Goal treatment compared to the Neutral treatment.

Hypothesis 3a. Output quantity will not decrease in the Charisma without goal treatment compared to the Neutral treatment.

[16] This assumption is also driven by the fact that we did not find a negative relationship between quantity and quality of work in our first study.

Hypothesis 3b. Output quality will not decrease in the Charisma without goal treatment compared to the Neutral treatment.

4.2 Design

4.2.1 Work task

The workers transcribed historic documents from the Frick Collection and Frick Art Reference Library Archives. All documents are typed letters written in English. The transcribed documents will become part of the collection and will be accessible and searchable by researchers and the general public.[17] The task, therefore, has a clear meaning and adds value and at the same time also requires effort and attention to detail. We divided all letters into fragments and constructed 15 batches of fragment groups. Each batch consists of a sequence of fragments, where the length of a fragment (i.e., its number of characters) at a given position in the sequence is roughly constant across all batches. In each treatment workers were randomly assigned to one of the batches. We let 20 workers work on the same batch to provide us with sufficient data for quality control. As in Study 1, workers could type fragments for a total duration of ten minutes. They received one fragment at a time on the screen and got a new fragment after each submission.

4.2.2 Treatments

We again use a between-subject design to systematically investigate the impact of motivational techniques, in particular, charismatic leadership tactics, including quantitative output goals, on worker performance. We conducted four treatments labeled *Neutral*, *Goal*, *Charisma without goal*, and *Full charisma*, which differ by the written instructions workers receive prior to work. All treatment instructions contained the same information about the nature of the task and are of similar length. Workers in the *Neutral* treatment received standard instructions informing them about the purpose of their work, the collaboration with the Frick Collection and Frick Art Reference Library Archives, and that they would be working together with other workers to preserve historic documents. The complete instructions for each treatment can be found in Section 6.3 of the Appendix.

The *Charisma without goal* treatment differed from the *Neutral* treatment only in that instructions have been written in a more charismatic way using verbal charismatic leadership tactics (CLT) according to Antonakis et al. (2011, 2012) wherever possible. Inspired by Antonakis et al. (2019), in particular we employed metaphors, rhetorical questions, stories, three-part-lists, moral conviction, and raised sentiments of the collective. For example, in *Neutral* we wrote: *Your effort will help the project. Each fragment you manage to transcribe will translate into one more data point. Together with hundreds of other MTurkers working on this*

[17] We are grateful that the Frick Collection and Frick Art Reference Library Archives have agreed to collaborate with us.

HIT, your work will contribute to preserve and build knowledge of past events. By contrast, in *Charisma without goal* the message is: *You might think, will my extra effort really help? Yes, it will! Each fragment is like a little piece of a puzzle; together with hundreds of other MTurkers, you will put the puzzle together. You can bring history to life and keep it alive. Just like historians, you contribute to preserve and build the public knowledge of past events.* We did not use goal-related CLTs or explicitly state a quantitative goal in this treatment.

The *Goal* treatment is identical to the *Neutral* treatment but contains an additional paragraph where we communicate a quantitative output goal. In particular, we add the two CLTs "setting high and ambitious goals" and "creating confidence that the goal can be achieved" to the instructions of the *Neutral* treatment. We provide workers with the additional information that workers in similar HITs previously managed to transcribe 25 fragments on average and we ask them to score at least 34 fragments. Reaching the goal translates to being among the top 28% performers in the pilot study.[18] Moreover, we clarify that scoring 34 fragments was a challenging yet achievable goal. We also told workers that we were confident they would reach their goal because of their work experience.

The *Full charisma* treatment combines the non-goal related charismatic leadership tactics from the *Charisma without goal* treatment and the goal related CLTS from the *Goal* treatment in the instructions. The *Full charisma* treatment therefore contains the most CLTs from all our treatments and triggers "frame and vision" as well as "substance." The resulting 2x2 treatment design is summarized in Table 6.

[Table 6 about here]

4.2.3 Sample and procedures

A total of 1800 workers participated in our second study. We posted the same job advertisement on MTurk for a data entry task that we used in Study 1 with the only difference being that we raised the fixed payment to \$3.[19] Our selection criteria (98% approval rate or higher, at least 500 previously approved HITs, location U.S.) remain also unchanged. We excluded workers that had participated in previous sessions of Study 1 or the pilot study we used to determine the goal for our Goal treatment.[20] After workers accepted the HIT, they followed a

[18] The goal was determined based on a pilot study with 120 workers who worked on the *Neutral* treatment. Based on our findings for the reference point intervention in Study 1, we chose a rather ambitious goal to avoid demotivating high performers. At the same time, we were reluctant to raise the bar even further because low performers might choke under the pressure and perceive the goal as unreachable, which was not the aim of our intervention.

[19] We raised the fixed payment to ensure compliance with the minimum wage requirements in the U.S.. In addition, workers spend on average 14 minutes and 18 seconds on the task and the survey which is roughly one minute more compared to Study 1.

[20] One worker accepted the invitation but never actually worked on the task and is therefore missing from the sample. In addition, the timer of the work task did not work properly for 31 workers who we exclude from the analysis. All excluded observations are unrelated to any

link to Qualtrics which hosts our study. All workers were randomly allocated to treatments and could work on the task for ten minutes. Afterwards they completed a short survey containing questions on demographics, information on the device used for working on the study, touch typing ability, familiarity with Frick Collection and Frick Art Reference Library Archives, questions on motivation, identification with the mission to preserve historic documents, and the impact of the Covid-19 pandemic on work life.

[Table 7 about here]

Table 7 provides an overview of the background characteristics of subjects participating in Study 2. Workers were, on average, 38 years old and possessed a four year college degree. About four percent used a mobile device to complete the task. The sample also contains an equal number of male and female workers. Importantly, we observe that the treatments were balanced with respect to all of these characteristics.[21] Figure S4 in the Appendix also shows that workers spend, on average, the same amount of time reading the intervention messages they receive before beginning to work.

4.2.4 Objective manipulation check

We executed an objective manipulation check to evaluate the absolute number of charismatic leadership tactics in our instructions (see Antonakis et al. (2019); Meslec et al. (2020) for a similar approach). Note that we do not aim at evaluating the perception of charisma in our manipulation check. The objective manipulation check was executed by external evaluators in order to avoid workers becoming aware of the different instructions and possibly adjusting their behavior (see Lonati et al., 2018). The check was done by two trained research assistants who independently coded each treatment instruction. The research assistants were instructed to mark the occurrence of the verbal charismatic leadership tactics on sentence level (see Tables S11, S12, S13 in the Appendix). We calculated the intercoder reliability for each treatment. For the *Neutral* treatment (n=15 sentences) the coders agreed on 99.26% of the coding events (15 sentences x 9 charismatic leadership tactics). The agreement level can be tested against chance agreement using Cohen's kappa with $\kappa = 0.85$, $se = 0.085$, $z = 10.02$ and $p < 0.01$ revealing a substantial or almost perfect alignment of coders for all treatment interventions (see Landis and Koch, 1977). The agreement percentage is 96.73% for the *Charisma without goal* treatment (n=17 sentences with $\kappa = 0.74$, $se = 0.081$, $z = 9.22$ and $p < 0.01$)), 98.15% for the *Goal* treatment (n=18 sentences with $\kappa = 0.76$, $se = 0.078$, $z = 9.70$ and $p < 0.01$)) and 96.11% for the *Full charisma* treatment (n=20 sentences with $\kappa = 0.72$, $se = 0.075$, $z = 9.66$ and $p < 0.01$)). The agreement rates are rather similar for each treatment and both coders reconciled their coding after having coded individually until they reached an agreement.

treatment condition.

[21] We report results from balance tests in Table S9.

4.3 Results

4.3.1 Quantity

For analysing the output quantity of our workers, we again first focus on differences between distributions of the number of fragments submitted before assessing differences in the average number of fragments per worker. Figure 6 plots the inverse cumulative distribution function (ICDF) for the number of submitted fragments for each treatment. We find that the ICDF from the *Full charisma* treatment, where we combine goal-related and non-goal related CLTs, lies furthest to the right of all ICDFs and stochastically dominates the distribution of submitted fragments relative to all other treatments we employ (KS, two sided, vs. *Charisma without goal*: $p < 0.001$, vs. *Goal*: $p = 0.029$ and vs. *Neutral*: $p = 0.038$, respectively). This indicates that the combination of goal-related and non-goal related CLTs results in the highest overall output quantity. In contrast, we find that the ICDF from the *Charisma without goal* treatment lies furthest to the left, suggesting that the isolated use of non goal-related CLTs yields the lowest output quantity among all treatments.[22]

[Figure 6 about here]

Similar to Study 1, we estimate the average treatment effects of our interventions on worker output by using ordinary least squares (OLS) regressions with robust standard errors and employ a series of nested versions for the following specification for our 2x2 factorial design:

$$\begin{aligned} Y_i = \beta_0 &+ \beta_1 Goal\ CLT_i + \beta_2 Non\text{-}Goal\ CLT_i \\ &+ \beta_3 Goal\ CLT_i \times Non\text{-}Goal\ CLT_i + \gamma X_i + \delta G_i + \varepsilon_i \end{aligned} \tag{2}$$

where Y captures the number of submitted fragments and *Goal CLT* is an indicator variable for treatments that employ goal-related CLTs including a quantitative goal. *Non-Goal CLT* is an indicator variable for the use of non-goal related CLTs, X_i is a vector of background characteristics for each worker i, G_i is a vector of indicator variables for each fragment group and ε_i is an error term.

In the saturated regression specification, the coefficient for the *Goal CLT* variable captures differences in average output between the *Goal* treatment and the *Neutral* baseline. The coefficient for the *Non-Goal CLT* variable reflects differences in average output between the *Charisma without goal* treatment and the *Neutral* baseline. On the other hand, the *Full charisma* treatment effect on average output relative to the *Neutral* baseline can be estimated by adding the coefficients of *Goal CLT*, *Non-Goal CLT*, and the interaction term denoted by *Goal CLT* × *Non-Goal CLT*.

Model I in Table 8 reports main effect estimates result. Here, the *Goal CLT* coefficient can be interpreted as measuring the average marginal effect on output

[22] We fail to identify any statistically significant dominance relationship for any pairwise comparison of ICDFs from the *Goal*, *Charisma without goal*, and *Neutral* treatment.

for treatments that make use of goal related CLTs (*Goal* and *Full charisma*) relative to treatments that do not make any use of goal related CLTs (*Neutral* and *Charisma without goal*). The *Non-Goal CLT* coefficient, on the other hand, reveals the average marginal effect on output using non-goal related CLTs and a broad set of CLTs (*Charisma without goal* and *Full charisma*) against treatments not using non-goal related CLTs (*Goal* and *Neutral*). We find a statistically significant average marginal effect of 1.71 fragments ($p < 0.001$) when we compare treatments employing goal related CLTs to treatments without these goal-related CLTs. We also find an overall positive, albeit insignificant average marginal effect of using non-goal related CLTs and using a broad set of CLTs compared to treatments without non-goal related CLTs ($p = 0.624$).

Model II in Table 8 reports main and interaction effect estimates without additional background variables as controls or fragment group specific intercepts. We find that the average output per worker is not affected by using goal related CLTs ($p = 0.718$), rendering our *Goal* treatment intervention ineffective to enhance performance (no support for Hypothesis 2a). In contrast, we identify a negative effect on average output of using non-goal related CLTs (no suppport for Hypothesis 3a). Specifically, employing charismatic leadership tactics without including output goals significantly decreases average worker performance by 1.691 fragments relative to the *Neutral* baseline ($p = 0.027$).

Whereas the use of goal and non-goal related CLTs in isolation has no or even negative effects on average worker productivity, we find a positive and statistically significant interaction effect of combining these two leadership tactics ($p < 0.001$). In particular, relative to the baseline, average output increases by 2 fragments ($p = 0.014$) to the highest average output per worker of 31.33 fragments when we employ the full set of CLTs in the *Full charisma* treatment (support for Hypothesis 1a). This can be seen from the estimate for the linear combination of the *Goal CLT* + *Non-Goal CLT* + *Goal CLT* × *Non-Goal CLT* that we report under the main estimates in Table 8.

Table 8 also reports linear combinations estimating the marginal effect of introducing goal related CLTs to workers when non-goal related CLTs are already applied (*Goal CLT* + *Goal CLT* × *Non-Goal CLT*), as well as the linear combinations capturing the marginal effect of introducing non-goal related CLTs to workers when goal related CLTs are already present (*Non-Goal CLT* + *Goal CLT* × *Non-Goal CLT*). We find that the former increases output by 3.69 fragments whereas the latter increases output by 2.29 fragments (both $p < 0.01$), highlighting the complementary effect on productivity of both sets of leadership tactics.

Models III and IV add a set of worker background variables and fragment group specific intercepts, respectively, and show that results remain robust to the inclusion of these variables. Background variables include gender, age, education, and device used for the work task. From the set of background variables, we find that older workers submit, on average, fewer fragments whereas more educated workers and females show a higher work performance in the task. Using a mobile device in the text transcription task decreases work performance significantly.[23]

4.3.2 Quality

For assessing the quality of each submitted fragment, we compute the Levenshtein edit distance to the correct fragment and then normalize the distance to obtaining an error rate per fragment.[24] Following the regression specification in Equation (2), Table 9 presents results from a series of nested random-effects panel regressions, where the dependent variable in each regression captures the error rate of a submitted fragment the worker submitted.[25]

Model I reports main effect estimate results of using non-goal related CLTs and goal related CLTs, whereas Models II, III and IV also include interaction effects, background characteristics of workers as controls and intercepts for different fragment groups, respectively. Overall, we find that workers submit fragments that have an average error rate of about 0.020 ($p < 0.001$) independent of their treatment affiliation. We cannot identify any statistically significant main or interaction effect on the average quality of work (no support for Hypotheses 1b, 2b, and 3b). From the set of background variables, we find that female workers submit, on average, fragments with a smaller error rate, whereas mobile users deliver fragments that are significantly more error prone.[26]

[Table 9 about here]

We again investigate whether workers who submit a larger number of fragments deliver low-quality work because they neglect the quality dimension of their task. Figure 7 plots the completion rate for each worker, that is the number of submitted fragments as a share of the total number of fragments a worker could submit (110 in total), against the average error rate for all submitted fragments by treatment.

[Figure 7 about here]

We fail to identify any significant positive linear relationship between the share of submitted fragments a worker submits and their average error rate. Instead, we find that, in all treatments, workers who produce more fragments also submit fragments that are characterized by a lower average error rate.[27]

[23] In Table S14 we also provide estimates for fragment group specific intercepts not reported in Table 8.

[24] We compare the entered output of the workers to determine the correct spelling of the fragment. If we have only one observation for a fragment, we let a research assistant type the fragment as well to allow us to control for quality.

[25] We report means and standard deviations for the average error rate in Figure S6.

[26] In Table S15 we also provide estimates for fragment group specific intercepts not reported in Table 9.

[27] Table S16 in the Appendix shows regression results for regressing the averaged error rate per worker on the share of the total number of fragments a worker could submit. We allow for intercepts and slope parameters to vary across treatments separately as well as in combination. We identify no qualitative differences in slope or intercept parameters across treatments.

We make use of a randomized instrumental variables approach to test whether average fragment quality is unaffected by changes in average output as a result of our treatment interventions, or whether the relationship depicted in Figure 7 is purely associational. In particular, we employ the same 2SLS estimation procedure and treat quantity as the endogenous regressor to predict quality. Our treatment variables serve again as our instruments.

Results of the estimation are shown in Table 10. Model I shows OLS estimation results which indicate that an increase in the completion rate is associated with a statistically significant lower average error rate ($p < 0.001$). Specifically, the size of the estimate reveals that a one percentage point increase in a worker's completion rate relates to a lower average error rate of 0.089 percentage points.

Models II and III report the 2SLS results with Model II presenting the first- and Model III the second stage estimation results, respectively. First stage results show the negative effect of non-goal related CLTs and using the broad set of CLTs including goals. The partial F-statistic shows that our set of instruments is sufficiently correlated with the suspected endogenous regressor ($F(3, 1768) = 25.312, p < .001$) and exceeds critical values for testing the relevance of instruments (Stock and Yogo, 2005). Moreover, a Sargan-Hansen test of overidentifying restrictions is not significant ($\chi^2(2) = 0.117, p = 0.943$), giving support to the validity of our instruments.

The estimate results from the second stage reveal a negative, albeit statistically insignificant relationship between the completion rate and average error rate with about the same magnitude as the OLS estimate. The similarity of OLS and 2SLS estimates is reflected by statistically insignificant Wu-Hausman ($F(1, 1760) = 0.112, p = 0.738$) and Durbin scores ($\chi^2 = 0.112, p = 0.737$), lending support to the hypothesis that our OLS estimation yields consistent estimates. Overall, both OLS and 2SLS fail to reveal any statistically significant positive relationship between a worker's completion rate and the average error rate. We therefore conclude that changes in quantity as a result of our interventions do not come at the expense of lower average fragment quality in our second study.

4.4 Discussion

In Study 2, we investigate if the effects of the non-monetary interventions in our first study can be replicated or if verbal charismatic leadership techniques can trigger higher performance in an online labor market.

Study 1 has shown that providing a reference point for output quantity had no significant effects on average output quantity or quality. This result is backed up by our second study, where our *Goal* treatment did not significantly affect average performance relative to the *Neutral* baseline. We again formulated a quantitative goal but also provided substance by justifying the chosen goal and expressing confidence that the goal is challenging but achievable for the workers. We stated clearly on what we based the goal, namely on the output of other workers in previous sessions. In addition, we provided information about the average output of other workers (25 fragments) to set a challenging reference point at 34 fragments. To raise workers' self-efficacy belief, we also expressed our confidence that they will be able to reach the goal. Nevertheless, we did not find any performance effects, which indicates that a goal related subset of CLTs that aim at providing only "substance" but that cannot address "frame and vision" is not sufficient to trigger the perception of charisma in our setting. In contrast to our results on the reference point message in Study 1, we did not find evidence for an effort-harmonizing effect of the goal message in Study 2.

The *Charisma without goal* treatment encompasses a subset of CLTs aimed at providing "frame and vision" and to a lesser extent "substance", because we did not use goal related CLTs in this treatment. We expected this intervention to have a positive or neutral impact on both performance dimensions. However, the results show that this intervention leads to lower output than the *Neutral* treatment and thus backfires. We observed a similar pattern in the *Praise* treatment of Study 1. We conclude that, when we only employ a subset of CLTs such that the category "substance" is underrepresented, workers perceive our written instructions not as intended. Using such a subset of CLTs even turns out to be harmful for the employer because it reduces quantity considerably. We can only speculate about the underlying reasons for this finding. Maybe workers perceive an intervention that lacks important elements of substance in the form of specific goals as not authentic and artificial, in particular if the leader communicates only in writing. This possible explanation is supported by our findings in the *Full charisma* treatment.

We implement all CLTs from the *Charisma without goal* and the *Goal* treatments in the *Full charisma* treatment, making use of a broad set of charismatic communication tactics triggering both categories, "frame and vision" as well as "substance." This intervention leads to a considerable increase in output quantity and we observe a strong complementarity between goal related CLTs and other verbal CLTs. Our results indicate that, in an online setting, it is important to use a set of CLTs that covers both verbal categories of charismatic leadership as broadly as possible. Quantitative goals may provide focus and align effort of the workers towards a common target, but we also need to provide "frame and vision" to raise the workers' attention and add more substance to the message by using, for instance, sentiments of the collective or moral convictions to justify the mission. Using only "frame and vision" oriented CLTs can dramatically backfire whereas the use of only goal-related CLTs seems to be too weak to raise output levels. However, the output-enhancing effect of the broad set of pure verbal CLTs including goal-related and non-goal related CLTs in an online labor market setting with written communication only is impressive and shows the power of well-balanced communication even in the absence of non-verbal cues such as facial expressions and tone of voice.

5 General discussion

Our results provide rich insights into the potential to motivate workers in online labors markets with either monetary rewards, or by applying communication techniques, in particular short upfront messages and charismatic leadership tactics. In the following, we discuss some general findings and limitations of our two studies.

With respect to monetary rewards, we show that they do work to some extent, but that a higher piece rate does not lead to higher output in our set-up. This result is important because, holding fixed payments constant, higher monetary rewards entail higher costs of labor and higher payments for each delivered unit. Employers are therefore better off if they implement a rather low piece rate, at least in our setting. However, we offer a rather generous fixed payment to our workers in both studies, which might have already motivated workers to some extent so that monetary rewards were rendered less effective. Future studies should explore whether lower fixed payments or even pure piece rate settings lead to similar performance patterns. It would be interesting to see if multitasking problems are absent also for other types of tasks.

Interestingly, praising workers for their past good performance or using only a subset of non-goal related verbal CLTs backfired in our studies, whereas the usage of a broad CLT set led to a substantial increase in delivered output. Our findings indicate that employers in online labor markets need to pay attention to what and how they communicate. An unreflected usage of praise or non-goal related subsets of CLTs can even be harmful and result in lower performance. In order to evoke the positive effect associated with charismatic communication, employers need to use a broad set of CLTs addressing both categories, "frame and vision" as well as "substance", properly. Our study reveals that goal-related CLTs and non-goal related verbal CLTs are complements and work well even in an online setting with written messages only. Future research should explore if and how other combinations of verbal CLTs work in online labor markets.

Overall, the strong impact of charismatic communication on output levels in an online labor market with a spot contract and purely written one-way communication from employer to worker is impressive. Usually, non-verbal cues contribute highly to being perceived as a charismatic leader and the usage of verbal and non-verbal techniques of charisma correlate quite strongly (Antonakis et al., 2011). However, in our online setting where written upfront communication is usually the only channel of interaction between employers and workers, the use of non-verbal techniques does not seem necessary to achieve a value-based, symbolic, and emotion-laden signaling by the employer. The reason might be that online workers do not expect such non-verbal cues.

We contribute to the leadership literature that tests leadership theories empirically. We present a series of large-scale field experiments using randomization, that allow for causal inference. Leadership has been extensively studied in psychology and management, which has led to numerous important insights, but many studies exhibit methodological problems that confine feasible conclusions.

In particular, field studies predicting outcomes from measured leadership styles typically do not use experimental interventions, but rather measure the effect of endogenously determined leadership styles (Antonakis et al., 2010). More specifically, there is not much evidence that varying how a leader communicates has a causal impact on workers' performance. Our paper thus contributes to the small literature that identifies casual effects of leader communication on worker behavior. Kvaløy et al. (2015) demonstrate that a simple motivational speech in a face-to-face setting increases both quantity and quality of output, but only if workers also receive monetary rewards. Antonakis et al. (2019) and Meslec et al. (2020) concentrate on charismatic leadership techniques and use tasks with inherent moral value. Both present evidence that CLTs can raise workers' output when workers listen to a leader's speech, delivered either in person or via video including non-verbal tactics. Meslec et al. (2020) demonstrate that this positive effect only occurs in their study if there is a congruence between the leaders' and the followers' values. In contrast to these papers, we study the effects of monetary rewards and soft leadership techniques in an online labor market where workers typically receive only written messages from the leader and the tasks at hand do not posses a clear inherent moral value. In addition, our paper further enhances our knowledge about potential interactions between monetary rewards and soft leadership techniques. Previous papers presenting causal evidence have found positive (Kvaløy et al., 2015) or no interactions (Kosfeld et al., 2017; Meslec et al., 2020).

Our results also advance and inform leadership theory. By testing the charismatic leadership theory as defined by Antonakis et al. (2016), we contribute to the generalizability of this theory (see also Antonakis et al. (2019) and Meslec et al. (2020)). In particular, we show that the concept can be replicated across operationalizations (different speeches and tasks), follower types (students and workers), and environments (online vs. offline). Antonakis et al. (2019) and Meslec et al. (2020) both implement a task with an inherent moral value (helping sick children or contributing to a charity), where the moral righteousness was straightforward. Our transcription task lacks such a clear moral righteousness and is thus closer to standard work tasks that have a purpose but do not build on a universal belief. We provide evidence that CLTs work in a pure online setting, extending the finding of Meslec et al. (2020), who test the impact of video recorded communication. Taken together, these results indicate that virtual charismatic leadership is possible in certain environments. Moreover, our results can inspire further research on charismatic leadership theory. We disentangle charismatic tactics and test them separately, which allows us to explore the effectiveness of different tactics and their interaction.

On a more general level, our results demonstrate the need to develop leadership theories that to a larger extent take into account in which environments leadership takes place. For instance, it may well be the case that the availability of communication channels influences followers' expectations on appropriate leader communication. We find that the lack of non-verbal cues does not matter in a pure online setting, which may, however, not be true for other settings where non-verbal techniques are at the leader's disposal. Our results may thus suggest that leadership theory should not only incorporate the environment in which leadership takes place, but also put emphasis on the technological communication constraints that the leaders are facing.

Our main aim was to study leadership tactics in online labor markets. The lack of repeated interaction and personal relationships between worker and employer therefore also limits the generalizability of our results. The same tactics that do or do not work in our setting, may still work in other settings. In particular, one may want to test our digital interventions in more standard organizational contexts. As they stand, our results can mainly inform us about online labor markets. However, by introducing our interventions and methodology to richer organizational contexts, one may also inform virtual leadership outside the online labor market domain. For example, the e-leadership literature asserts that leadership can be particularly effective in the virtual domain (e.g., Avolio et al., 2000; Purvanova and Bono, 2009). In contrast to the setting we study, e-leadership research typically focuses on how to influence members of virtual project teams who regularly and repeatedly engage in computer-mediated communication with one another and their leader.

6 Conclusion

In contrast to employees within traditional firms, workers in online labor markets usually work on their own and have no face-to-face contact with employers and coworkers. Communication between worker and employer is typically one-sided and delivered in written instructions of the work task before the worker starts with the assigned task. This setting makes motivating online workers more challenging than motivating workers in traditional employment relationships, which typically entail frequent face-to-face interactions. In this paper we have presented results from two large scale experiments on MTurk, investigating the effect of piece rates and different forms of written communication on quality and quantity of the delivered work.

Our results reveal that monetary rewards work in online labor markets but there is no positive relationship between higher piece rates and output levels. Upfront motivational messages in the form of praise or only subsets of non-goal related verbal CLTs backfire and lead to a significant reduction in output, whereas the provision of goals or reference points do not lead to significant changes in average performance. Importantly, we find that using a broad set of verbal charismatic leadership tactics, including goal-related CLTs, enhances performance significantly even though non-verbal tactics such as facial expressions, body language, and animated voice are completely missing in our written set-up.

We do not find significant changes in the delivered quality in any of our treatment interventions. Thus, there is no evidence of a multitasking problem in our online labor market setting. Given that the employers usually rely on the workers to deliver high quality, this finding is very promising for posting work in online labor markets. Indeed, we do not observe a negative correlation between quantity and quality in this online labor market.

As a final reflection, people nowadays work from home more frequently than in the past, and digital communication and online meetings substitute for physical presence also in traditional employment relationships. The Covid-19 pandemic has further boosted remote work, and it is expected that companies will at least partially continue their new work practices after the pandemic (The Economist, 2020). Leaders are thus increasingly expected to motivate their workforce digitally, with fewer communication techniques at their disposal. Our results and methodology, using randomised controlled trials and structured simple interventions, can inspire more research on both the perils and potentials of digital motivation and leadership.

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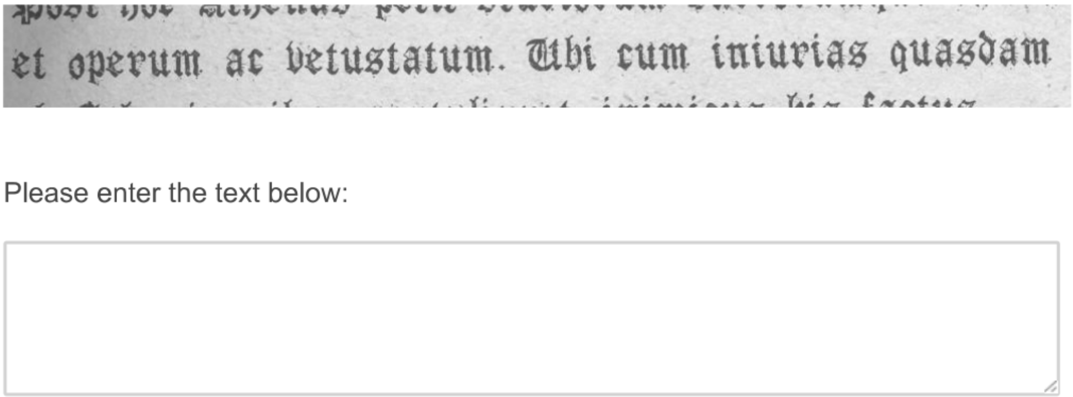
Figure 1: Screenshot of the work task, Study 1



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Note: The picture shows an example fragment from the task used in Study 1 that workers had to transcribe.

Table 1: Treatment table, Study 1

	Non-monetary intervention			
Performance pay	No message	Praise	Reference point	All
No piece rate	300	292	299	891
Low piece rate	295	301	295	891
High piece rate	302	297	299	898
All	897	890	893	2680

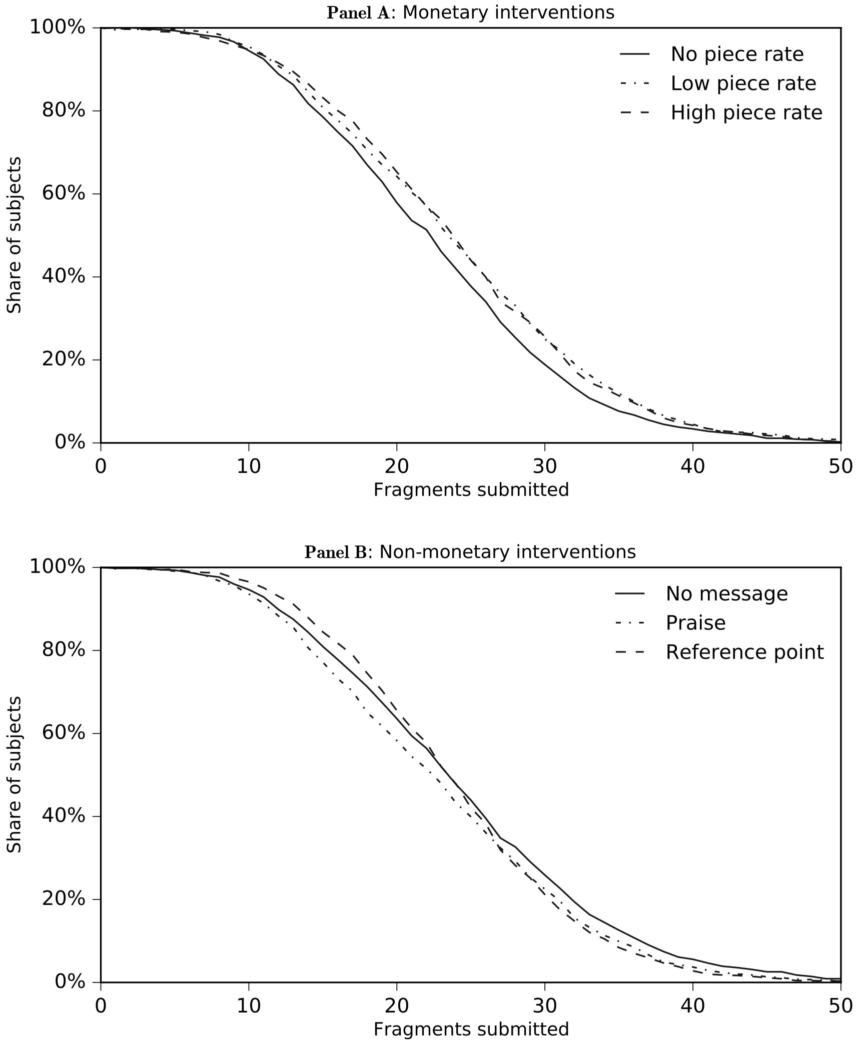
Note: The table gives an overview of the experimental design of Study 1 and shows the combination of the monetary and non-monetary treatment interventions. The number of subjects for each treatment cell is indicated as well.

Table 2: Background characteristics of subjects, Study 1

		Age	Female	Education	Mobile device	Latin	
Performance pay	**Non-monetary intervention**	**Mean (se)**	**Mean (se)**	**Mean (se)**	**Mean (se)**	**Mean (se)**	**N**
No piece rate	No message	36.28 (0.59)	0.50 (0.03)	3.12 (0.08)	0.05 (0.01)	1.42 (0.04)	300
	Praise	36.04 (0.62)	0.50 (0.03)	3.24 (0.08)	0.03 (0.01)	1.38 (0.04)	292
	Reference point	35.77 (0.65)	0.54 (0.03)	3.12 (0.07)	0.07 (0.01)	1.44 (0.04)	299
Low piece rate	No message	35.87 (0.64)	0.50 (0.03)	3.08 (0.07)	0.07 (0.01)	1.41 (0.04)	295
	Praise	34.49 (0.56)	0.50 (0.03)	3.07 (0.08)	0.04 (0.01)	1.41 (0.04)	301
	Reference point	35.42 (0.64)	0.49 (0.03)	3.15 (0.08)	0.03 (0.01)	1.45 (0.05)	295
High piece rate	No message	34.93 (0.61)	0.46 (0.03)	3.02 (0.08)	0.05 (0.01)	1.46 (0.04)	302
	Praise	35.15 (0.64)	0.52 (0.03)	3.13 (0.07)	0.06 (0.01)	1.40 (0.04)	297
	Reference point	36.08 (0.65)	0.54 (0.03)	3.09 (0.08)	0.05 (0.01)	1.47 (0.05)	299
All		35.56 (0.21)	0.50 (0.01)	3.11 (0.03)	0.05 (0.00)	1.43 (0.01)	2680
$P(> F)$		0.405	0.637	0.740	0.137	0.850	

Note: The table reports background characteristics of subjects participating in Study 1. Subjects were recruited through the Amazon Mechanical Turk crowdsourcing platform. "Age" is a continuous variable measuring participants' age in years; "Female" captures the proportion of females; "Education" is an ordinally scaled variable: 1 = High School', 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; "Mobile device" captures the share of mobile users; "Latin" is an ordinarily scaled variable measuring the subject's knowledge of Latin: 1 = Not at all, 5 = Very well. Reported are also p-values for the overall regression F-statistic from models in which the respective background characteristic is regressed on all treatment indicator variables.

Figure 2: Fragments submitted, Study 1



Note: The figure plots the inverse cumulative distribution function for the number of submitted fragments in all treatments with no, a low, or a high piece rate (Panel A) and all treatments with no message, a praise message, or a reference point message (Panel B).

Table 3: Treatment effects on quantity, Study 1

Model	I	II	III
Dependent variable:	No. Fragment	No. Fragment	No. Fragment
Low piece rate	1.398***	1.950**	1.978***
	(0.422)	(0.780)	(0.748)
High piece rate	1.418***	2.190***	1.968***
	(0.415)	(0.737)	(0.718)
Praise	-1.215***	-1.075	-1.260*
	(0.438)	(0.730)	(0.703)
Reference point	-0.332	0.847	0.781
	(0.417)	(0.690)	(0.669)
Low piece rate		-0.272	-0.474
× Praise		(1.082)	(1.041)
High piece rate		-0.153	0.092
× Praise		(1.045)	(1.015)
Low piece rate		-1.379	-1.610*
× Reference point		(1.020)	(0.974)
High piece rate		-2.160**	-1.960**
× Reference point		(0.999)	(0.968)
Age			-0.193***
			(0.015)
Female			0.728**
			(0.334)
Education			0.529***
			(0.131)
Mobile device			-5.022***
			(0.863)
Latin			0.960**
			(0.374)
Constant	22.718***	22.277***	27.225***
	(0.384)	(0.505)	(0.831)
N	2680	2680	2680
R^2	0.009	0.011	0.084
F	5.752	3.458	18.757
$P(> F)$	0.000	0.001	0.000

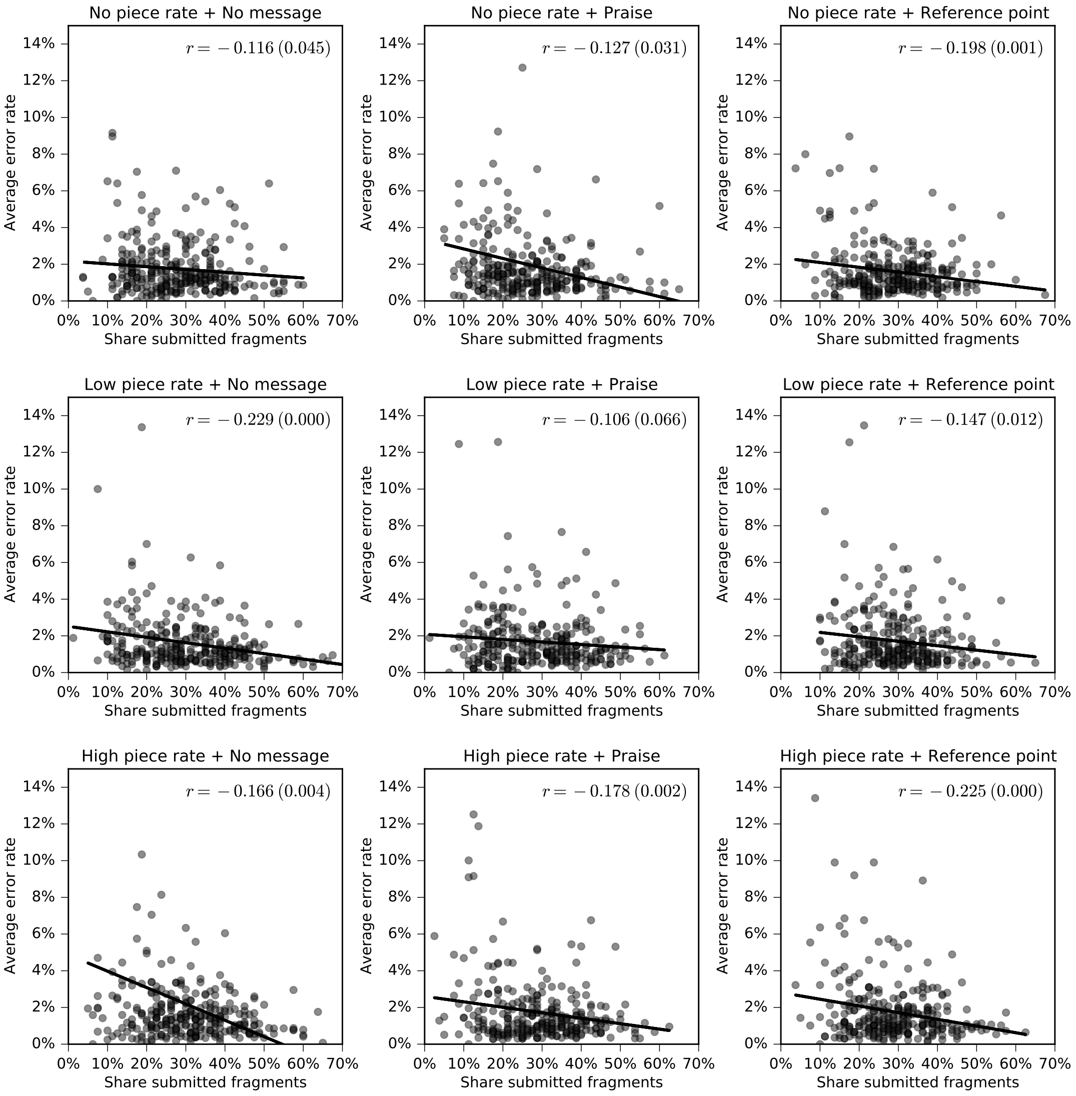
Note: The table reports estimation results for regressions in which the number of fragments submitted per worker is regressed on a set of explanatory variables. "Low piece rate": indicator variable taking the value of one if the treatment used a low piece rate. "High piece rate": indicator variable taking the value of one if the treatment used a high piece rate. "Praise": indicator variable taking the value of one if the treatment praised workers. "Reference point": indicator variable taking the value of one if the treatment set a reference point. "Age": continuous variable measuring a worker's age. "Female": indicator variable taking the value one if the worker is a female. "Education" is an ordinally scaled variable: 1 = High School, 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; "Mobile device": indicator variable taking the value one if the worker used a mobile device. "Latin": indicator variable taking the value of one if the worker has at least some knowledge of Latin. Robust standard errors in parentheses; $^{*}: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$.

Table 4: Treatment effects on quality, Study 1

Model	I	II	III
Dependent variable:	Error rate	Error rate	Error rate
Low piece rate	-0.001	-0.001	-0.002
	(0.001)	(0.002)	(0.002)
High piece rate	0.001	0.004	0.003
	(0.002)	(0.002)	(0.002)
Praise	-0.000	0.002	0.002
	(0.002)	(0.003)	(0.003)
Reference point	-0.001	-0.002	-0.001
	(0.001)	(0.002)	(0.002)
Low piece rate		-0.001	-0.001
× Praise		(0.003)	(0.003)
High piece rate		-0.006	-0.006
× Praise		(0.004)	(0.004)
Low piece rate		0.003	0.003
× Reference point		(0.003)	(0.003)
High piece rate		-0.002	-0.002
× Reference point		(0.003)	(0.003)
Age			-0.000
			(0.000)
Female			-0.004***
			(0.001)
Education			-0.001*
			(0.000)
Mobile device			0.008**
			(0.003)
Latin			0.000
			(0.001)
Constant	0.018***	0.017***	0.021***
	(0.001)	(0.002)	(0.003)
N	62026	62026	62026
R^2	0.002	0.002	0.002
R^2 (Within)	0.000	0.000	0.000
R^2 (Between)	0.001	0.003	0.013

Note: The table reports estimation results from random effects panel regressions in which the error rate per fragment and worker is regressed on a set of explanatory variables. “Low piece rate”: indicator variable taking the value of one if the treatment used a low piece rate. “High piece rate”: indicator variable taking the value of one if the treatment used a high piece rate. “Praise”: indicator variable taking the value of one if the treatment praised workers. “Reference point”: indicator variable taking the value of one if the treatment set a reference point. “Age”: continuous variable measuring a worker’s age. “Female”: indicator variable taking the value one if the worker is a female. “Education” is an ordinally scaled variable: 1 = High School, 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree.“Mobile device”: indicator variable taking the value one if the worker uses a mobile device. “Latin”: indicator variable taking the value of one if the worker has at least some knowledge of Latin. Robust standard errors in parentheses; $^{*}: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$.

Figure 3: Quantity vs. quality, Study 1



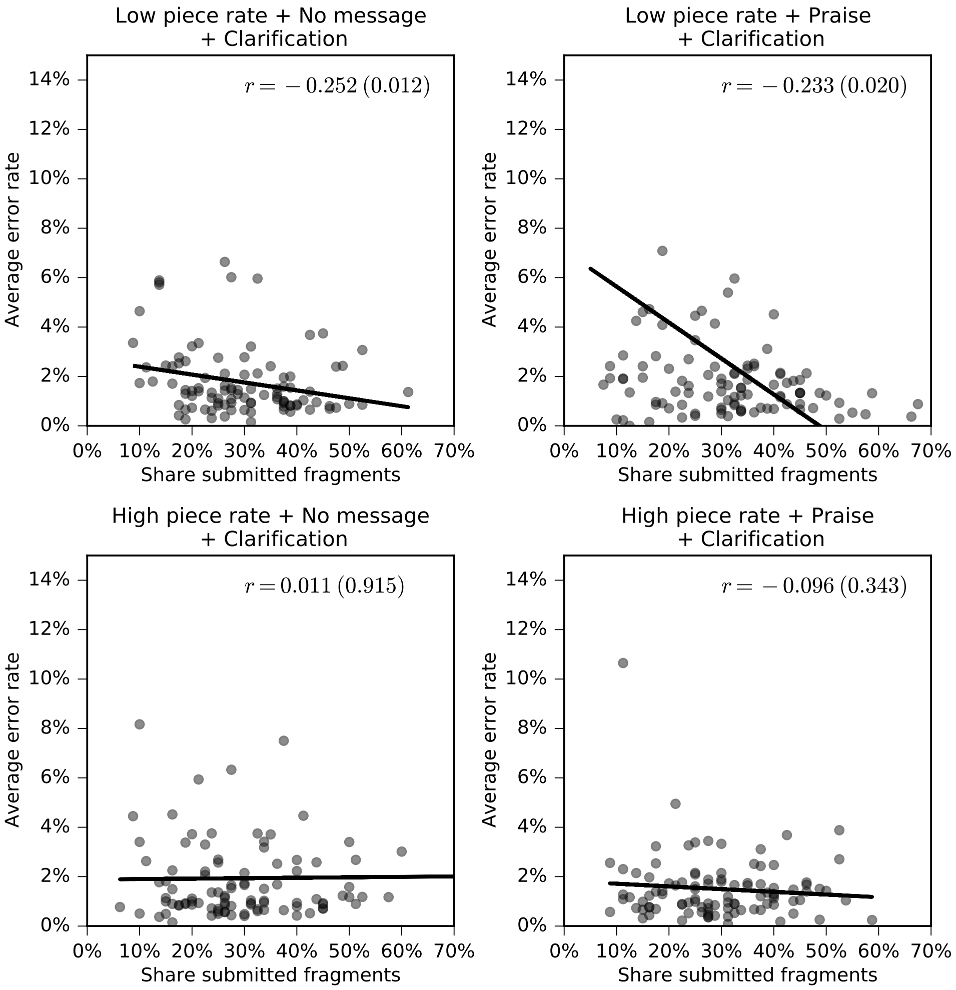
Note: The figure plots the number of submitted fragments per worker as a percentage of the total number of fragments a worker could submit against the average error rate for all submitted fragments per worker for each treatment combination. Indicated as well are the overlaid linear predictions as well as the Pearson correlation coefficient along with p-values (in parentheses).

Table 5: Instrumental variable estimation, Study 1

Model	OLS	2SLS	
		1st stage	2nd stage
Dependent variable:	Avg. error rate	Share fragments	Avg. error rate
Share fragments	-0.036***		-0.019
	(0.007)		(0.073)
Age	-0.000	-0.002***	-0.000
	(0.000)	(0.000)	(0.000)
Female	-0.004***	0.009**	-0.004***
	(0.001)	(0.004)	(0.001)
Education	-0.000	0.007***	-0.001
	(0.000)	(0.002)	(0.001)
Mobile device	0.006**	-0.063***	0.007
	(0.002)	(0.011)	(0.005)
Latin	-0.000	0.012**	-0.000
	(0.001)	(0.005)	(0.002)
Constant	0.034***	0.340***	0.029
	(0.004)	(0.011)	(0.025)
Low piece rate		0.025***	
		(0.009)	
High piece rate		0.025***	
		(0.009)	
Praise		-0.016*	
		(0.009)	
Reference point		0.001	
		(0.008)	
Low piece rate		-0.006	
× Praise		(0.013)	
High piece rate		0.001	
× Praise		(0.013)	
Low piece rate		-0.020*	
× Reference point		(0.012)	
High piece rate		-0.025**	
× Reference point		(0.012)	
N	2680	2680	2680
R^2	0.027	0.084	0.024
Partial F-statistic		30.48***	
Wu-Hausman F			0.204
Durbin χ^2			0.204
Sargan χ^2			8.248

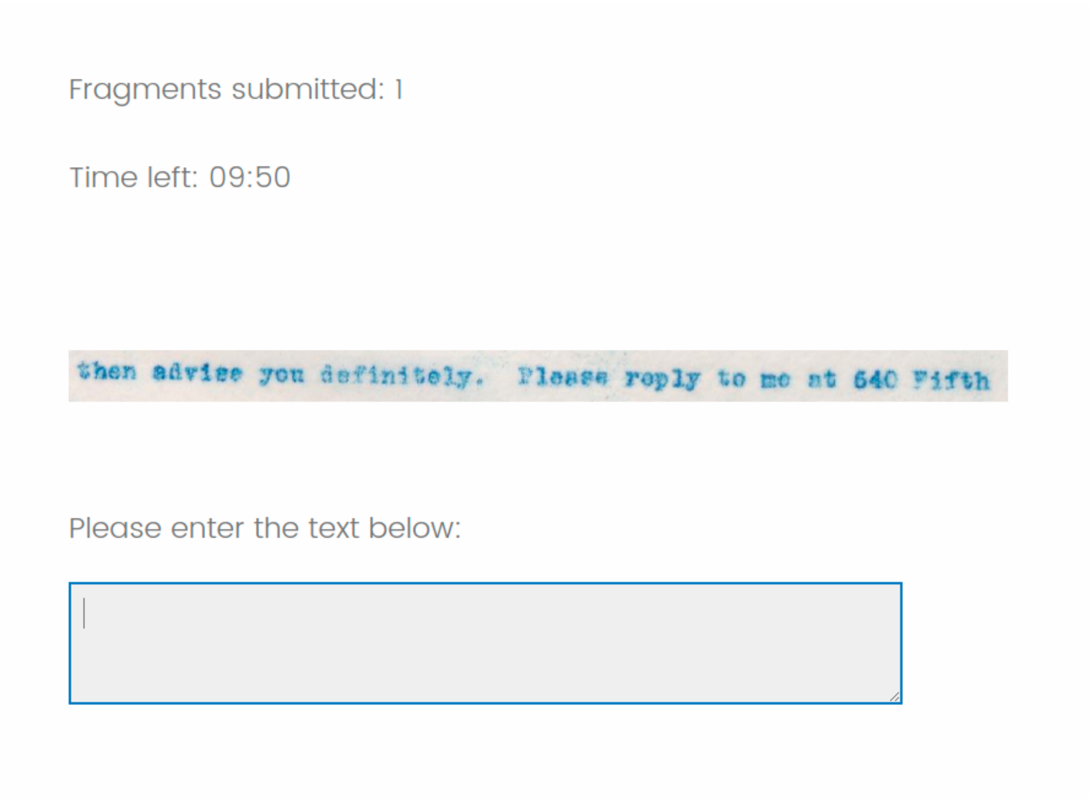
Note: The table reports OLS and 2SLS estimation results for regressions in which the time averaged error rate for each worker is regressed against the number of submitted fragments as a share of the total number of fragments a worker could submit ("Share fragments"). "Age": continuous variable measuring a worker's age. "Female": indicator variable taking the value one if the worker is a female. "Education" is an ordinally scaled variable: 1 = High School, 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; "Mobile device": indicator variable taking the value one if the worker uses a mobile device. "Latin": indicator variable variable taking the value of one if the worker has at least some knowledge of Latin. "Low piece rate": indicator variable taking the value of one if the treatment used a low piece rate. "High piece rate": indicator variable taking the value of one if the treatment used a high piece rate. "Praise": indicator variable taking the value of one if the treatment praised workers. "Reference point": indicator variable taking the value of one if the treatment set a reference point. Robust standard errors in parentheses; * : $p < 0.1$, ** : $p < 0.05$, *** : $p < 0.01$.

Figure 4: Quantity vs. quality, clarification treatments only, Study 1



Note: The figure plots the number of submitted fragments per worker as a percentage of the total number of fragments a worker could submit against the average error rate for all submitted fragments per worker for each clarification treatment. Indicated as well are the overlaid linear predictions as well as the Pearson correlation coefficients along with p-values (in parentheses).

Figure 5: Screenshot of the work task, Study 2



Fragments submitted: 1

Time left: 09:50

then advise you definitely. Please reply to me at 640 Fifth

Please enter the text below:

Note: The picture shows an example fragment from the task used in Study 2 that workers had to transcribe.

Table 6: Treatment table, Study 2

	Non-Goal related CLTs		
Goal related CLTs	No	Yes	All
No	444	442	886
Yes	438	444	882
All	882	886	1768

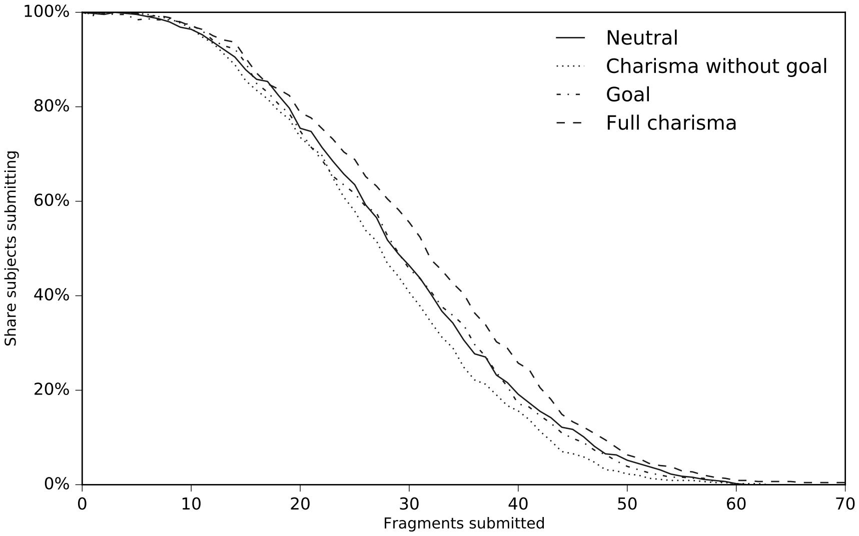
Note: The table gives an overview of the experimental design of Study 2 and shows the combination of non-goal related charismatic leadership tactics (CLTs) and goal-related CLT treatment interventions. The number of subjects for each treatment cell is indicated as well.

Table 7: Background characteristics of subjects, Study 2

		Age	**Education**	**Female**	**Mobile device**	
Non-goal rel. CLT	**Goal rel. CLT**	**Mean (se)**	**Mean (se)**	**Mean (se)**	**Mean (se)**	**N**
No	No	37.29 (0.54)	4.57 (0.06)	0.51 (0.02)	0.03 (0.01)	444
	Yes	37.69 (0.55)	4.42 (0.06)	0.48 (0.02)	0.03 (0.01)	442
Yes	No	37.76 (0.55)	4.45 (0.06)	0.46 (0.02)	0.06 (0.01)	438
	Yes	37.88 (0.55)	4.52 (0.06)	0.47 (0.02)	0.03 (0.01)	444
All		37.65 (0.27)	4.49 (0.03)	0.47 (0.01)	0.04 (0.00)	1768
$P(> F)$		0.88	0.33	0.27	0.22	

Note: The table reports background characteristics of subjects participating in Study 2. Subjects were recruited through the Amazon Mechanical Turk crowd-sourcing platform. "Age" is a continuous variable measuring participants' age in years; "Female" captures the proportion of females; "Education" is an ordinally scaled variable: 1 = High School', 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; "Mobile device" captures the share of mobile users. Reported also are p-values for differences in the overall regression F-statistic from a model in which the respective background characteristic is regressed on all treatment indicator variables.

Figure 6: Fragments submitted, Study 2



Note: The figure plots the inverse cumulative distribution function for the number of submitted fragments in all treatments.

Table 8: Treatment effects on quantity, Study 2

Model:	I	I	II	III
Dependent variable:	No. Fragment	No. Fragment	No. Fragment	No. Fragment
Goal CLT	1.711***	-0.285	0.292	0.252
	(0.559)	(0.789)	(0.746)	(0.741)
Non-Goal CLT	0.296	-1.691**	-1.551**	-1.654**
	(0.559)	(0.763)	(0.731)	(0.732)
Goal CLT × Non-Goal CLT		3.983***	3.507***	3.585***
		(1.115)	(1.064)	(1.065)
Age			-0.204***	-0.202***
			(0.022)	(0.022)
Female			1.839***	1.870***
			(0.535)	(0.532)
Diverse			4.404	3.781
			(3.503)	(3.848)
Education			0.495**	0.476**
			(0.205)	(0.203)
Mobile device			-13.608***	-13.458***
			(0.924)	(0.968)
Constant	28.335***	29.327***	34.174***	30.293***
	(0.485)	(0.559)	(1.331)	(1.569)
Goal CLT		3.698***	3.800***	3.837***
+ Goal CLT × Non-Goal CLT		(0.787)	(0.759)	(0.761)
Non-Goal CLT		2.292***	1.956**	1.931**
+ Goal CLT × Non-Goal CLT		(0.813)	(0.774)	(0.769)
Goal CLT + Non-Goal CLT		2.007**	2.249***	2.183***
+ Goal CLT × Non-Goal CLT		(0.814)	(0.779)	(0.773)
N	1768	1768	1768	1768
R^2	0.005	0.013	0.103	0.126
F	4.734	7.408	40.894	16.163
$P(> F)$	0.009	0.000	0.000	0.000

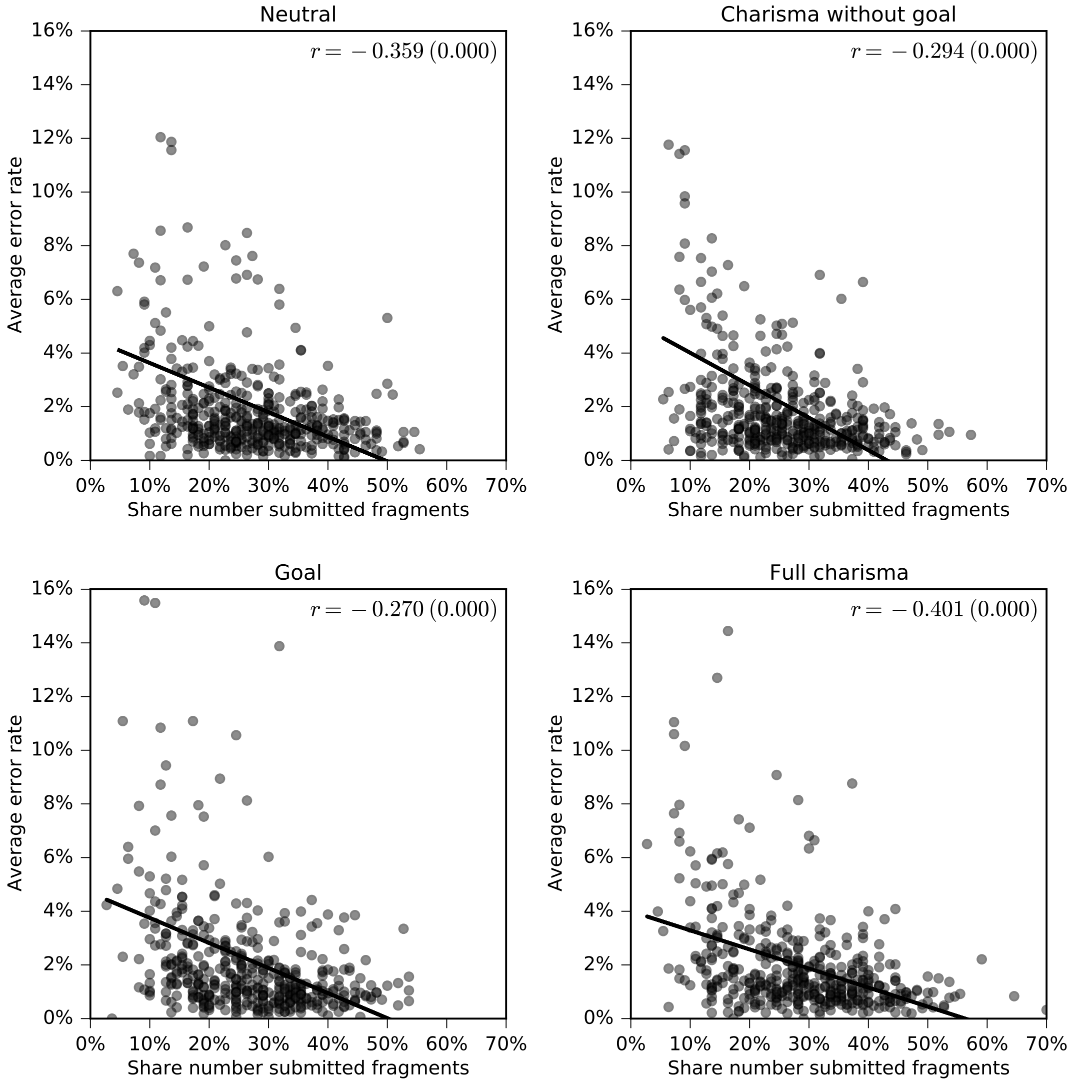
Note: The table reports linear regression results of the number of fragments submitted per worker on a set of explanatory variables. "Goal CLT": indicator variable taking the value of one if the treatment uses goal-related CLTs. "Non-Goal CLT": indicator variable taking the value of one if the treatment employed non-goal related CLTs. "Age": continuous variable measuring a worker's age. "Female": indicator variable taking the value one if the worker is a female. "Diverse": indicator variable taking the value one if the worker identifies as neither male nor female."Education" is an ordinally scaled variable: 1 = High School, 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; "Mobile device": indicator variable taking the value one if the worker used a mobile device. "Group intercepts": Indicates whether the model specification includes indicator variables for each fragment group (estimate results not reported here). Robust standard errors in parentheses ($^*: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$).

Table 9: Treatment effects on quality, Study 2

Model	I	II	III	IV
Dependent variable:	Error rate	Error rate	Error rate	Error rate
Goal CLT	-0.000	0.001	0.001	0.001
	(0.002)	(0.003)	(0.002)	(0.002)
Non-Goal CLT	-0.001	0.001	0.001	0.001
	(0.002)	(0.003)	(0.002)	(0.002)
Goal CLT × Non-Goal CLT		-0.003	-0.003	-0.003
		(0.003)	(0.003)	(0.003)
Age			-0.000	-0.000
			(0.000)	(0.000)
Female			-0.005***	-0.005***
			(0.002)	(0.002)
Diverse			-0.005	-0.005
			(0.008)	(0.008)
Education			0.001**	0.001**
			(0.000)	(0.000)
Mobile device			0.030***	0.031***
			(0.008)	(0.008)
Constant	0.021***	0.020***	0.019***	0.023***
	(0.002)	(0.002)	(0.004)	(0.005)
N	51868	51868	51868	51868
R^2	0.003	0.003	0.004	0.005
R^2 (Within)	0.000	0.000	0.000	0.000
R^2 (Between)	-0.000	0.000	0.047	0.067

Note: The table reports estimation results from random effects panel regressions in which the error rate per fragment and worker is regressed on a set of explanatory variables. “Goal CLT”: indicator variable taking the value of one if the treatment uses goal-related CLTs. “Non-Goal CLT”: indicator variable taking the value of one if the treatment employed non-goal related CLTs. “Age”: continuous variable measuring a worker’s age. “Female”: indicator variable taking the value one if the worker is a female. “Diverse”: indicator variable taking the value one if the worker identifies as neither male nor female. “Education” is an ordinally scaled variable: 1 = High School, 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; “Group intercepts”: Indicates whether the model specification includes indicator variables for each fragment group (estimate results not reported here). Robust standard errors in parentheses ($^{*}: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$).

Figure 7: Quality vs. quantity, Study 2



Note: The figure plots the number of submitted fragments per worker as a percentage of the total number of fragments a worker could submit against the average error rate for all submitted fragments per worker for each treatment. Indicated as well are the overlaid linear predictions as well as the Pearson correlation coefficient along with p-values (in parentheses).

Table 10: Instrumental variable estimation, Study 2

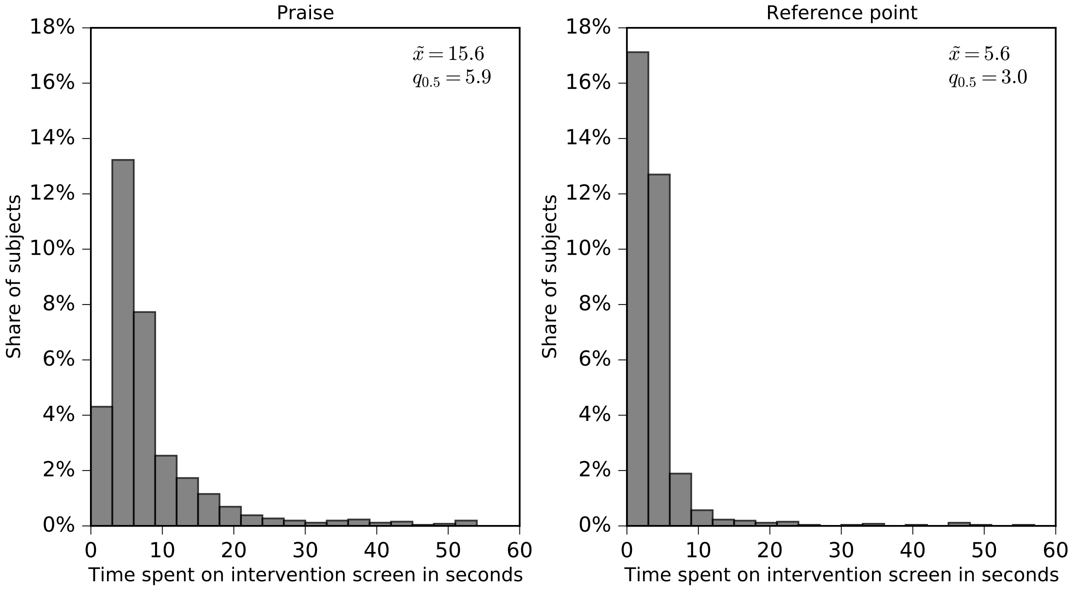
Model	OLS	2SLS	
		1st stage	2nd stage
Dependent variable:	Avg. error rate	Share fragments	Avg. error rate
Share fragments	-0.089***		-0.073
	(0.010)		(0.057)
Age	-0.000***	0.002***	-0.000
	(0.000)	(0.000)	(0.000)
Female	-0.004***	0.017***	-0.004***
	(0.002)	(0.005)	(0.002)
Diverse	-0.002	0.040	-0.002
	(0.004)	(0.003)	(0.004)
Education	0.002***	0.002**	0.002***
	(0.000)	(0.001)	(0.001)
Mobile device	0.020*	-0.122***	0.022*
	(0.011)	(0.008)	(0.012)
Constant	0.047***	0.310***	0.042**
	(0.005)	(0.012)	(0.018)
Goal CLT		0.003	
		(0.007)	
Non-Goal CLT		-0.014**	
		(0.007)	
Goal CLT×Non-Goal CLT		0.032***	
		(0.010)	
N	1768	1768	1768
R^2	0.126	0.103	0.122
Partial F-statistic		25.31***	
Wu-Hausman F			0.112
Durbin χ^2			0.112
Sargan χ^2			0.117

Note: The table reports OLS and 2SLS estimation results for regressions in which the time averaged error rate for each worker is regressed against the number of submitted fragments as a share of the total number of fragments a worker could submit ("Share fragments"). "Age": continuous variable measuring a worker's age. "Female": indicator variable taking the value one if the worker is a female. "Diverse": indicator variable taking the value one if the worker identifies as neither male nor female. "Education" is an ordinally scaled variable: 1 = High School, 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; "Mobile device": indicator variable taking the value one if the worker uses a mobile device. "Goal CLT": indicator variable taking the value of one if the treatment uses goal-related CLTs. "Non-Goal CLT": indicator variable taking the value of one if the treatment employed non-goal related CLTs. Robust standard errors in parentheses (* : $p < 0.1$, ** : $p < 0.05$, *** : $p < 0.01$).

Appendix

6.1 Additional tables and figures

Figure S1: Time spent on intervention screen, study 1



Note: The figure shows the histogram of time spent on the intervention screen for the treatments with a praise message (left panel) and the treatments with a reference point message (right panel). The mean ($\bar{x}$) and median ($q_{0.5}$) time spent on the intervention screen are reported in each panel as well.

Table S1: Balance test, Study 1

Dependent variable:	Age	Female	Education	Mobile device	Latin
No piece rate & Neutral	1.353	0.043	0.100	0.004	-0.034
	(0.853)	(0.041)	(0.109)	(0.017)	(0.061)
No piece rate & Praise	1.114	0.040	0.220**	-0.019	-0.077
	(0.870)	(0.041)	(0.108)	(0.015)	(0.060)
No piece rate & Reference point	0.842	0.082**	0.107	0.021	-0.012
	(0.891)	(0.041)	(0.104)	(0.019)	(0.061)
Low piece rate & Neutral	0.944	0.041	0.061	0.021	-0.050
	(0.888)	(0.041)	(0.106)	(0.019)	(0.059)
Low piece rate & Praise	-0.442	0.045	0.053	-0.006	-0.045
	(0.828)	(0.041)	(0.108)	(0.017)	(0.062)
Low piece rate & Reference point	0.490	0.035	0.136	-0.016	-0.009
	(0.889)	(0.041)	(0.108)	(0.016)	(0.063)
High piece rate & Praise	0.221	0.062	0.115	0.018	-0.056
	(0.890)	(0.041)	(0.104)	(0.019)	(0.058)
High piece rate & Reference point	1.150	0.082**	0.070	0.000	0.018
	(0.897)	(0.041)	(0.107)	(0.017)	(0.063)
Constant	34.930***	0.457***	3.017***	0.046***	1.457***
	(0.614)	(0.029)	(0.076)	(0.012)	(0.043)
N	2680	2680	2680	2680	2680
R^2	0.003	0.002	0.002	0.004	0.002
F	1.038	0.761	0.645	1.544	0.510
$P(> F)$	0.405	0.637	0.740	0.137	0.850

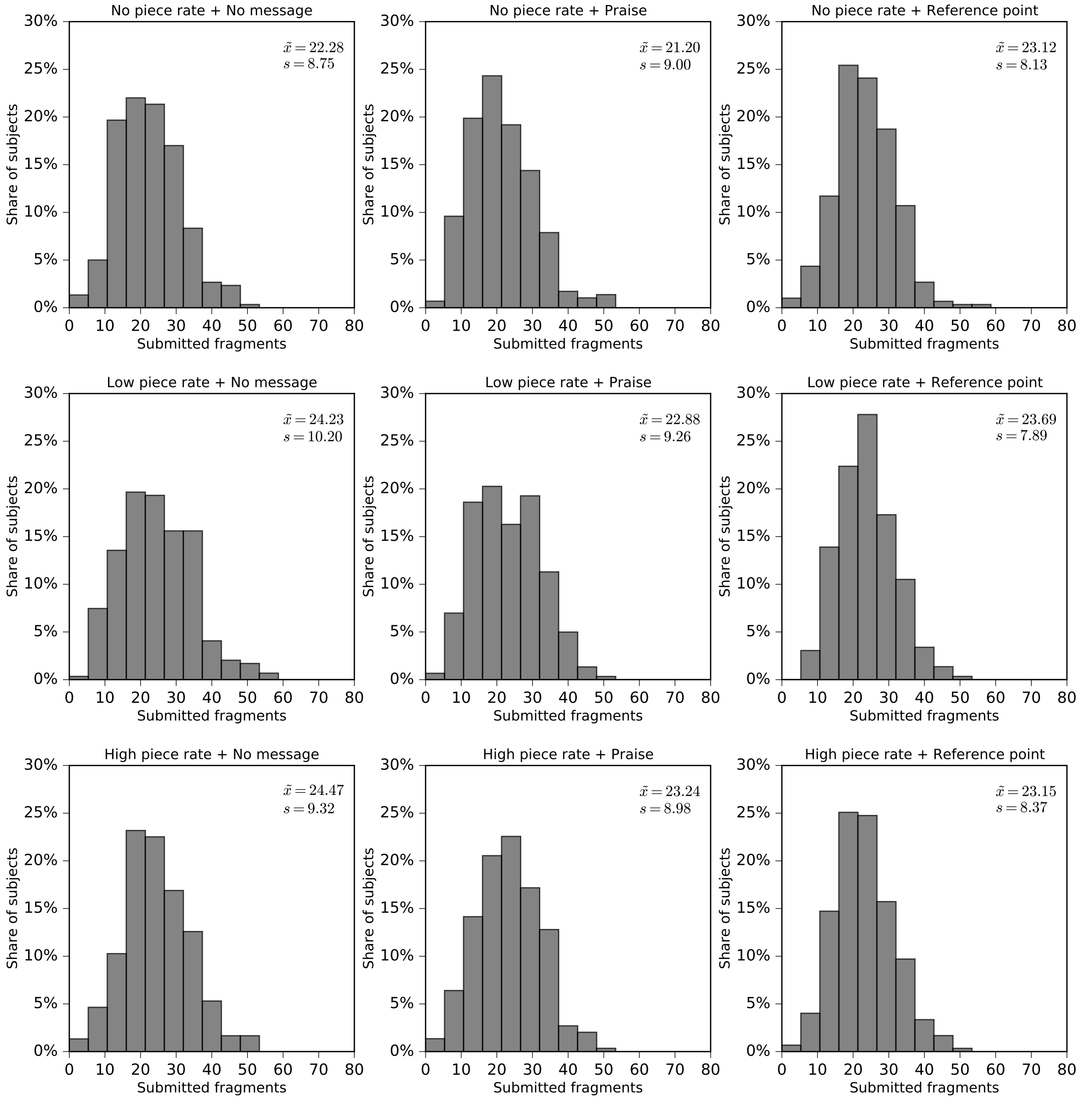
Note: The table reports estimation results for OLS regressions in which different background variables are regressed against a set of treatment indicator variables. The table also reports for each regression the p-value of the joint F-test for the hypothesis that all three treatment indicator variables are jointly different from zero *Baseline* treatment. "Age": continuous variable measuring a worker's age. "Female": indicator variable taking the value one if the worker is a female. "Education" is an ordinally scaled variable: 1 = High School, 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; "Mobile device": indicator variable taking the value one if the worker uses a mobile device. The Robust standard error in parentheses ($^* : p < 0.1$, $^{**} : p < 0.05$, $^{***} : p < 0.01$).

Table S2: Covariance table, Study 1

	Mean	Std.	No. frag- ments	Error rate	Low piece rate	High piece rate	Praise	Reference point	Low piece rate × Praise	High piece rate × Praise	Low piece rate × Refer- ence point	High piece rate × Refer- ence point	Age	Female	Education	Mobile device	Latin
No. fragments	23.14	8.94	1.0	-0.13***	0.04*	0.04**	-0.05***	0.01	-0.01	0.0	0.02	0.0	-0.22***	0.01	0.07***	-0.11***	0.05***
Avg. error rate	0.02	0.03	-0.13***	1.0	-0.02	0.03	0.01	-0.02	-0.01	-0.0	-0.01	-0.0	-0.01	-0.07***	-0.04*	0.06***	-0.02
Low piece rate	0.33	0.47	0.04*	-0.02	1.0	-0.5***	0.01	-0.0	0.5***	-0.25***	0.5***	-0.25***	-0.02	-0.01	-0.01	-0.01	-0.01
High piece rate	0.34	0.47	0.04**	0.03	-0.5***	1.0	-0.0	-0.0	-0.25***	0.5***	-0.25***	0.5***	-0.01	-0.0	-0.02	0.01	0.02
Praise	0.33	0.47	-0.05***	0.01	0.01	-0.0	1.0	-0.5***	0.5***	0.5***	-0.25***	-0.25***	-0.02	0.0	0.02	-0.02	-0-03
Reference point	0.33	0.47	0.01	-0.02	-0.0	-0.0	-0.5***	1.0	-0.25***	-0.25***	0.5***	0.5***	0.01	0.03	0.0	-0.0	0.02
Low piece rate ×*Praise*	0.11	0.32	-0.01	-0.01	0.5***	-0.25***	0.5***	-0.25***	1.0	-0.13***	-0.13***	-0.13***	-0.04*	-0.0	-0.01	-0.01	-0.01
High piece rate ×*Praise*	0.11	0.31	0.0	-0.0	-0.25***	0.5***	0.5***	-0.25***	-0.13***	1.0	-0.12***	-0.13***	-0.01	0.01	0.01	0.02	-0.01
Low piece rate ×*Referencepoint*	0.11	0.31	0.02	-0.01	0.5***	-0.25***	-0.25***	0.5***	-0.13***	-0.12***	1.0	-0.12***	-0.0	-0.01	0.01	-0.03	-0.01
High piece rate ×*Referencepoint*	0.11	0.31	0.0	-0.0	-0.25***	0.5***	-0.25***	0.5***	-0.13***	-0.13***	-0.12***	1.0	0.02	0.02	-0.01	-0.0	0.02
Age	35.56	10.75	-0.22***	-0.01	-0.02	-0.01	-0.02	0.01	-0.04*	-0.01	-0.0	0.02	1.0	0.14***	0.05***	-0.03	0.04**
Female	0.50	0.50	0.01	-0.07***	-0.01	-0.0	0.0	0.03	-0.0	0.01	-0.01	0.02	0.14***	1.0	0.02	0.0	-0.04*
Education	3.11	1.30	0.07***	-0.04*	-0.01	-0.02	0.02	0.0	-0.01	0.01	0.01	-0.01	0.05***	0.02	1.0	-0.03*	0.15***
Mobile device	0.05	0.22	-0.11***	0.06***	-0.01	0.01	-0.02	-0.0	-0.01	0.02	-0.03	-0.0	-0.03	0.0	-0.03*	1.0	0.01
Latin	0.31	0.46	0.05***	-0.02	-0.01	0.02	-0.03	0.02	-0.01	-0.01	-0.01	0.02	0.04**	-0.04*	0.15***	0.01	1.0

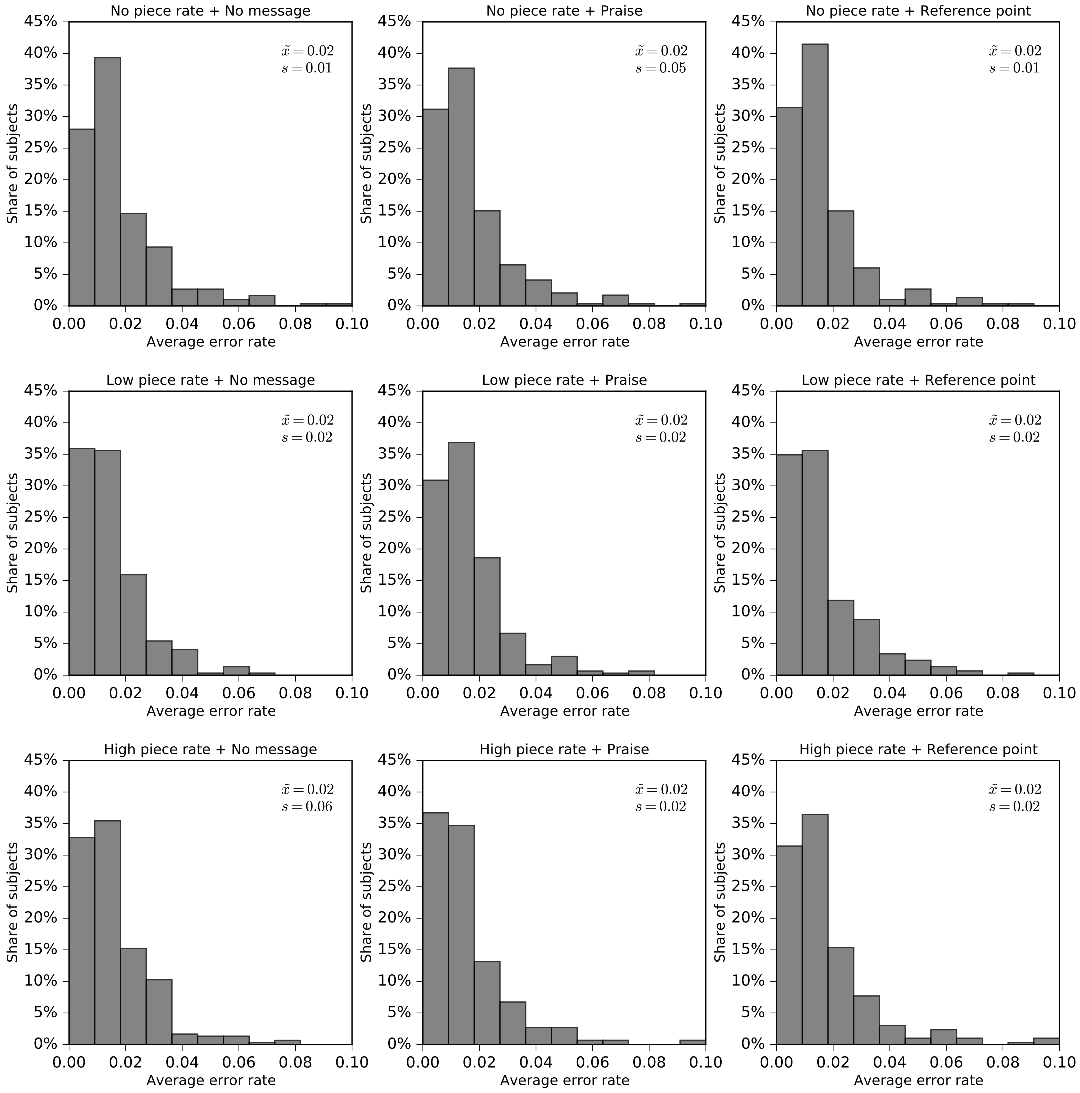
Note: The table reports means, standard deviations and covariances for variables used in the analysis. “Low piece rate”: indicator variable taking the value of one if the treatment used a low piece rate. “High piece rate”: indicator variable taking the value of one if the treatment used a high piece rate. “Praise”: indicator variable taking the value of one if the treatment praised workers. “Reference point”: indicator variable taking the value of one if the treatment set a reference point. “Age”: continuous variable measuring a worker’s age. “Female”: indicator variable taking the value one if the worker is a female. “Education” is an ordinally scaled variable: 1 = High School, 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; “Mobile device”: indicator variable taking the value one if the worker used a mobile device. “Latin”: indicator variable variable taking the value of one if the worker has at least some knowledge of Latin. * : $p < 0.1$, ** : $p < 0.05$, *** : $p < 0.01$.

Figure S2: Histogram fragments submitted, Study 1



Note: The figure shows the histogram for the number of submitted fragments in all treatments in study 1. Indicated as well are the mean ($\bar{x}$) and standard deviation (s).

Figure S3: Histogram error rate, Study 1



Note: The figure shows the histogram for the average error rate per worker in all treatments in study 1. Indicated as well are the mean ($\bar{x}$) and standard deviation (s).

Table S3: Quality vs. quantity, Study 1

Model	I	II	III	IV
Dependent variable:	Avg. error rate	Avg. error rate	Avg. error rate	Avg. error rate
Share fragments	-0.036***	-0.036***	-0.030***	-0.089*
	(0.007)	(0.007)	(0.006)	(0.048)
Constant	0.028***	0.032***	0.028***	0.049***
	(0.003)	(0.005)	(0.003)	(0.018)
Intercepts	No	Yes	No	Yes
Slopes	No	No	Yes	Yes
N	2680	2680	2680	2680
R^2	0.018	0.021	0.019	0.029
F	24.912	5.013	4.062	4.289
$P(> F)$	0.000	0.000	0.000	0.000

Note: The table reports estimation results for regressions in which the time averaged error rate per worker is regressed against the number of submitted fragments per worker as a percentage of the total number of fragments a worker could submit ("Share fragments"). Indicated as well is whether the model specification includes indicator variables for each treatment ("Intercepts") and treatment specific slopes ("Slopes") (estimate results not reported here). Robust standard error in parentheses ($^{*} : p < 0.1$, $^{**} : p < 0.05$, $^{***} : p < 0.01$).

Table S4: Quality vs. quantity, clarification treatments, Study 1

Model	I	II	III	IV
Dependent variable:	Avg. error rate	Avg. error rate	Avg. error rate	Avg. error rate
Share fragments	-0.050	-0.052	-0.043	0.002
	(0.035)	(0.036)	(0.037)	(0.015)
Constant	0.034***	0.035***	0.035***	0.019***
	(0.012)	(0.011)	(0.013)	(0.004)
Intercepts	No	Yes	No	Yes
Slopes	No	No	Yes	Yes
N	396	396	396	396
R^2	0.019	0.028	0.021	0.058
F	2.047	1.880	1.338	1.825
$P(> F)$	0.153	0.113	0.255	0.081

Note: The table reports estimation results for regressions in which the time averaged error rate per worker is regressed against the number of submitted fragments per worker as a percentage of the total number of fragments a worker could submit ("Share fragments"). Indicated as well is whether the model specification includes indicator variables for each treatment ("Intercepts") and treatment specific slopes ("Slopes") (estimate results not reported here). Robust standard error in parentheses ($^{*}: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$).

Table S5: Quality vs. quantity, clarification vs. no clarification, Study 1

Model	I	II	III
Dependent variable:	Avg. error rate	Avg. error rate	Avg. error rate
Share fragments	-0.042***	-0.040***	-0.041***
	(0.013)	(0.012)	(0.011)
Clarification		0.005	0.004
		(0.013)	(0.013)
Share fragments × Clarification		-0.010	-0.007
		(0.037)	(0.037)
Constant	0.031***	0.030***	0.038***
	(0.005)	(0.004)	(0.005)
Controls	No	No	Yes
N	1591	1591	1591
$R2$	0.018	0.019	0.026
F	11.169	4.927	4.730
$P(> F)$	0.001	0.002	0.000

Note: The table reports linear regression results for regressing the averaged error rate for all fragments on the number of submitted fragments per worker as a percentage of the total number of fragments a worker could submit ("Share fragments"). "Clarification": indicator variable taking the value one if workers received the information that we would not check the quality of their submitted fragments. Controls include variables for workers' age, gender, education, use of mobile device, and knowledge of Latin. Robust standard error in parentheses ($^{*}: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$).

Table S6: Treatment effects on quantity, with clarification treatments, Study 1

Model	I	II	III	IV	V
Dependent variable:	No. fragments	No. fragments	No. fragments	No. fragments	No. fragments
High piece rate	0.094			0.240	0.005
	(0.479)			(0.801)	(0.770)
Praise		-0.863*		-1.347*	-1.758**
		(0.479)		(0.799)	(0.767)
Clarification			0.269	-0.543	-0.712
			(0.564)	(1.068)	(1.032)
High piece rate × Praise				0.119	0.550
				(1.095)	(1.062)
High piece rate × Clarification				-0.087	0.469
				(1.600)	(1.528)
Praise × Clarification				2.473	2.732*
				(1.601)	(1.557)
High piece rate × Praise × Clarification				-1.532	-2.242
				(2.257)	(2.180)
Constant	23.723***	24.203***	23.703***	24.227***	30.083***
	(0.346)	(0.346)	(0.274)	(0.594)	(1.126)
Controls	No	No	No	No	Yes
N	1591	1591	1591	1591	1591
R^2	0.000	0.002	0.000	0.004	0.073

Note: The table reports linear regression estimation results from regressing the the number of fragments submitted per worker on a set of explanatory variables. "High piece rate": indicator variable taking the value one if workers received a high piece rate. "Praise": indicator variable taking the value one if workers received praise prior to work. "Clarification": indicator variable taking the value one if workers received the information that we would not check the quality of their submitted fragments. Controls include variables for workers' age, gender, education, use of mobile device, and knowledge of Latin. Robust standard errors in parentheses ($^* : p < 0.1$, $^{**} : p < 0.05$, $^{***} : p < 0.01$).

Table S7: Treatment effects on quality, with clarification treatments, study 1

Model	I	II	III	IV	V
Dependent variable:	Error rate	Error rate	Error rate	Error rate	Error rate
High piece rate	0.001			0.005	0.005
	(0.002)			(0.003)	(0.003)
Praise		-0.001		0.001	0.001
		(0.002)		(0.003)	(0.003)
Clarification			0.001	0.002	0.002
			(0.002)	(0.004)	(0.004)
High piece rate × Praise				-0.005	-0.005
				(0.005)	(0.005)
High piece rate × Clarification				-0.003	-0.004
				(0.005)	(0.005)
Praise × Clarification				0.007	0.006
				(0.007)	(0.007)
High piece rate × Praise × Clarification				-0.007	-0.007
				(0.009)	(0.009)
Constant	0.018***	0.019***	0.018***	0.016***	0.021***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)
Controls	No	No	No	No	Yes
N	37818	37818	37818	37818	37818
R^2	0.002	0.002	0.002	0.002	0.002
R^2 (Within)	0.000	0.000	0.000	0.000	0.000
R^2 (Between)	0.000	0.000	0.001	0.005	0.013

Note: The table reports random effects estimation results from regressing the error rate per fragment on a set of explanatory variables. "High piece rate": indicator variable taking the value one if workers received a high piece rate. "Praise": indicator variable taking the value one if workers received praise prior to work. "Clarification": indicator variable taking the value one if workers received the information that we would not check the quality of their submitted fragments. Controls include variables for workers' age, gender, education, use of mobile device and knowledge of Latin. Standard errors in parentheses ($^*: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$).

Table S8: Instrumental variable estimation, clarification treatments, Study 1

Model	OLS	2SLS	
		1st stage	2nd stage
Dependent variable:	Avg. error rate	Share fragments	Avg. error rate
Share fragments	-0.056		0.591
	(0.042)		(0.785)
Age	-0.000	-0.003***	0.001
	(0.000)	(0.001)	(0.002)
Female	-0.005*	0.033***	-0.026
	(0.003)	(0.012)	(0.029)
Education	0.001	0.006	-0.003
	(0.001)	(0.005)	(0.005)
Mobile device	0.000	-0.099***	0.063
	(0.008)	(0.033)	(0.080)
Latin	0.005	0.022*	-0.008
	(0.007)	(0.012)	(0.015)
Constant	0.046**	0.353***	-0.185
	(0.019)	(0.026)	(0.277)
High piece rate		0.008	
		(0.016)	
Praise		0.013	
		(0.017)	
High piece rate		-0.024	
×*Praise*		(0.024)	
N	396	396	396
R^2	0.031	0.099	-2.847
Partial F-statistic		0.153	
Wu-Hausman F			0.058*
Durbin χ^2			0.060*
Sargan χ^2			0.059

Note: The table reports OLS and 2SLS estimation results for regressions in which the time averaged error rate for each worker is regressed against the number of submitted fragments as a share of the total number of fragments a worker could submit ("Share fragments"). "Age": continuous variable measuring a worker's age. "Female": indicator variable taking the value one if the worker is a female. "Education" is an ordinally scaled variable: 1 = High School, 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; "Mobile device": indicator variable taking the value one if the worker uses a mobile device. "High piece rate": indicator variable taking the value one if workers received a high piece rate. "Praise": indicator variable taking the value one if workers received praise prior to work. Robust standard errors in parentheses ($^*: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$).

Table S9: Balance test, Study 2

Dependent variable:	Age	Female	Education	Mobile device
Charisma without Goal	0.406	-0.032	-0.158*	-0.004
	(0.765)	(0.034)	(0.088)	(0.012)
Goal	0.472	-0.050	-0.127	0.023*
	(0.769)	(0.034)	(0.087)	(0.014)
Full charisma	0.590	-0.056*	-0.056	0.000
	(0.765)	(0.034)	(0.088)	(0.012)
Constant	37.286***	0.507***	4.574***	0.034***
	(0.536)	(0.024)	(0.062)	(0.009)
N	1768	1768	1768	1768
R^2	0.000	0.002	0.002	0.003
F	0.225	1.135	1.318	1.470
$P(> F)$	0.88	0.33	0.27	0.22

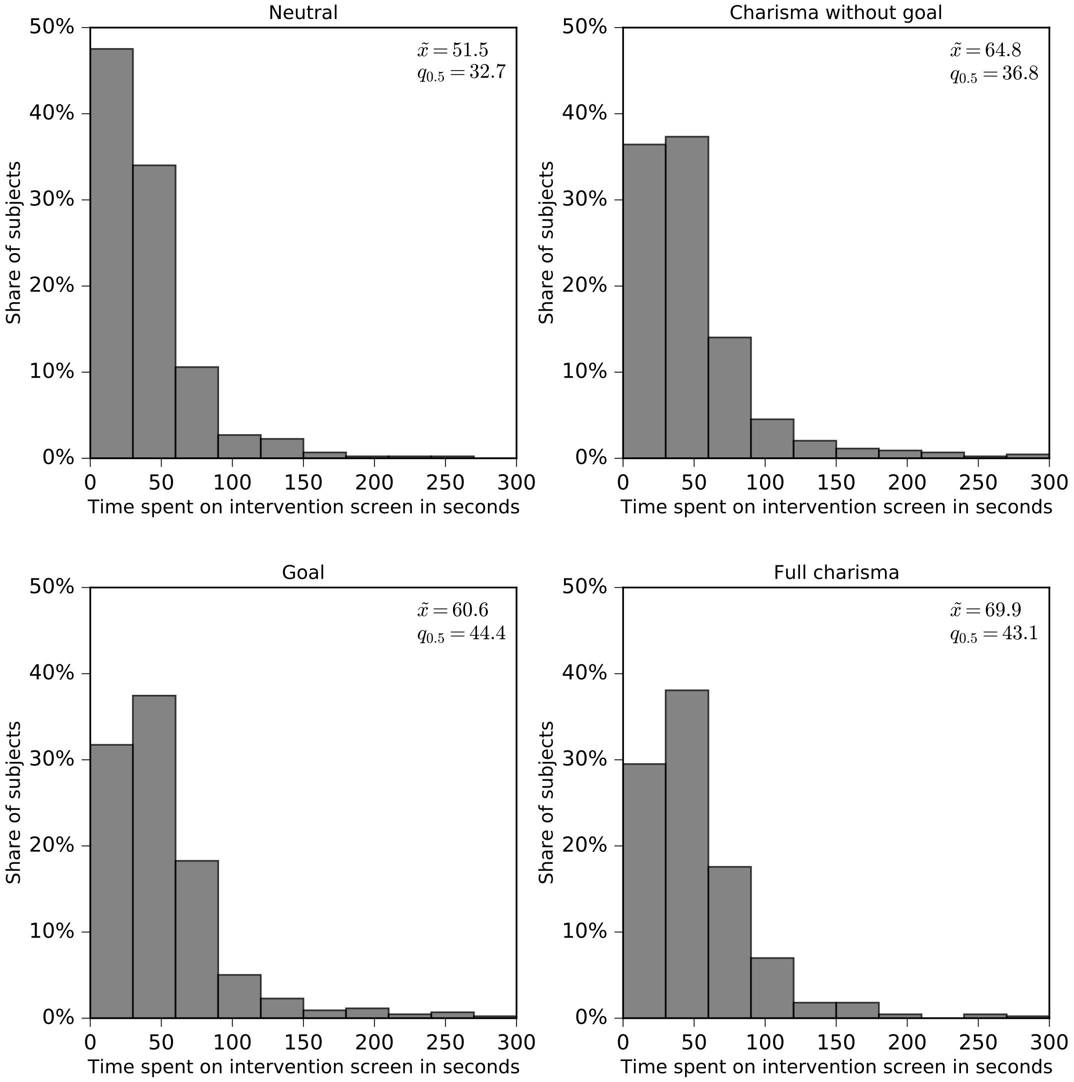
Note: The table reports estimation results for OLS regressions in which different background variables are regressed against a set of treatment indicator variables. The table also reports for each regression the p-value of the joint F-test for the hypothesis that all three treatment indicator variables are jointly different from zero *Baseline* treatment. "Age": continuous variable measuring a worker's age. "Female": indicator variable taking the value one if the worker is a female. "Education" is an ordinally scaled variable: 1 = High School, 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; "Mobile device": indicator variable taking the value one if the worker uses a mobile device. The Robust standard error in parentheses (* : $p < 0.1$, ** : $p < 0.05$, *** : $p < 0.01$).

Table S10: Covariance table, Study 2

	Mean	Std	No. fragments	Avg. error rate	Goal	Charisma without goal	Full charisma	Age	Female	Diverse	Education	Mobile device
No. fragments	29.34	11.78	1.0	-0.31***	0.07***	0.01	0.1***	-0.18***	0.05**	0.02	0.04*	-0.21***
Avg. error rate	0.02	0.03	-0.31***	1.0	-0.01	-0.01	-0.03	-0.04	-0.09***	0.0	0.06**	0.19***
Goal	0.50	0.50	0.07***	-0.01	1.0	0.0	0.58***	0.01	-0.04	-0.01	-0.0	0.04
Charisma without goal	0.50	0.50	0.01	-0.01	0.0	1.0	0.58***	0.01	-0.02	0.03	-0.02	-0.04
Full charisma	0.25	0.43	0.1***	-0.03	0.58***	0.58***	1.0	0.01	-0.03	0.01	0.01	-0.01
Age	37.65	11.44	-0.18***	-0.04	0.01	0.01	0.01	1.0	0.12***	-0.04	0.04*	-0.03
Female	0.47	0.50	0.05**	-0.09***	-0.04	-0.02	-0.03	0.12***	1.0	-0.07***	-0.04	-0.01
Diverse	0.01	0.08	0.02	0.0	-0.01	0.03	0.01	-0.04	-0.07***	1.0	0.02	0.02
Education	4.49	1.30	0.04*	0.06**	-0.0	-0.02	0.01	0.04*	-0.04	0.02	1.0	0.01
Mobile device	0.04	0.19	-0.21***	0.19***	0.04	-0.04	-0.01	-0.03	-0.01	0.02	0.01	1.0

Note: The table reports means, standard deviations and covariances for variables used in the analysis. “Goal”: indicator variable taking the value of one if the treatment uses goal-related CLTs. “Charisma without goal”: indicator variable taking the value of one if the treatment employed non-goal related CLTs. “Full charisma”: indicator variable taking the value of one if the treatment employed the complete set of CLTs. “Age”: continuous variable measuring a worker’s age. “Female”: indicator variable taking the value one if the worker is a female. “Diverse”: indicator variable taking the value one if the worker identifies as neither male or female.“Education” is an ordinally scaled variable: 1 = High School, 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; “Mobile device”: indicator variable taking the value one if the worker used a mobile device. $^{*}: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$.

Figure S4: Time spent on intervention screen, Study 2



Note: The figure shows the histogram of time spent on the intervention in all treatments for study 2. The mean ($\bar{x}$) and median ($q_{0.5}$) time spent on the intervention screen are reported in each panel as well.

Table S11: Categories and tactics, study 2

Framing and vision	C1	metaphors or similes, to simplify the message, stir emotions, and make parallels between symbolic meanings and realities more salient
	C2	rhetorical questions, to create intrigue and suspense, and direct attention to seeking the answer
	C3	stories and anecdotes, to simplify the message, trigger imagery and recall, engender identification with characters in the story, and identify a relevant moral
	C4	contrasts, to define what should be done versus what should not be done by showcasing the right way versus a wrong way
	C5	three-part lists, to provide sufficient proof or completeness
Substance	C6	expressing moral conviction, to focus attention on moral justification and on doing what is morally right
	C7	expressing the sentiments of the collective, to engender identification (via similarity) with the leader
	C8	setting high and ambitious goals, to make followers feel competent and focus their effort on a target
	C9	creating confidence that goals can be achieved, to raise follower confidence and make them more likely to exert effort

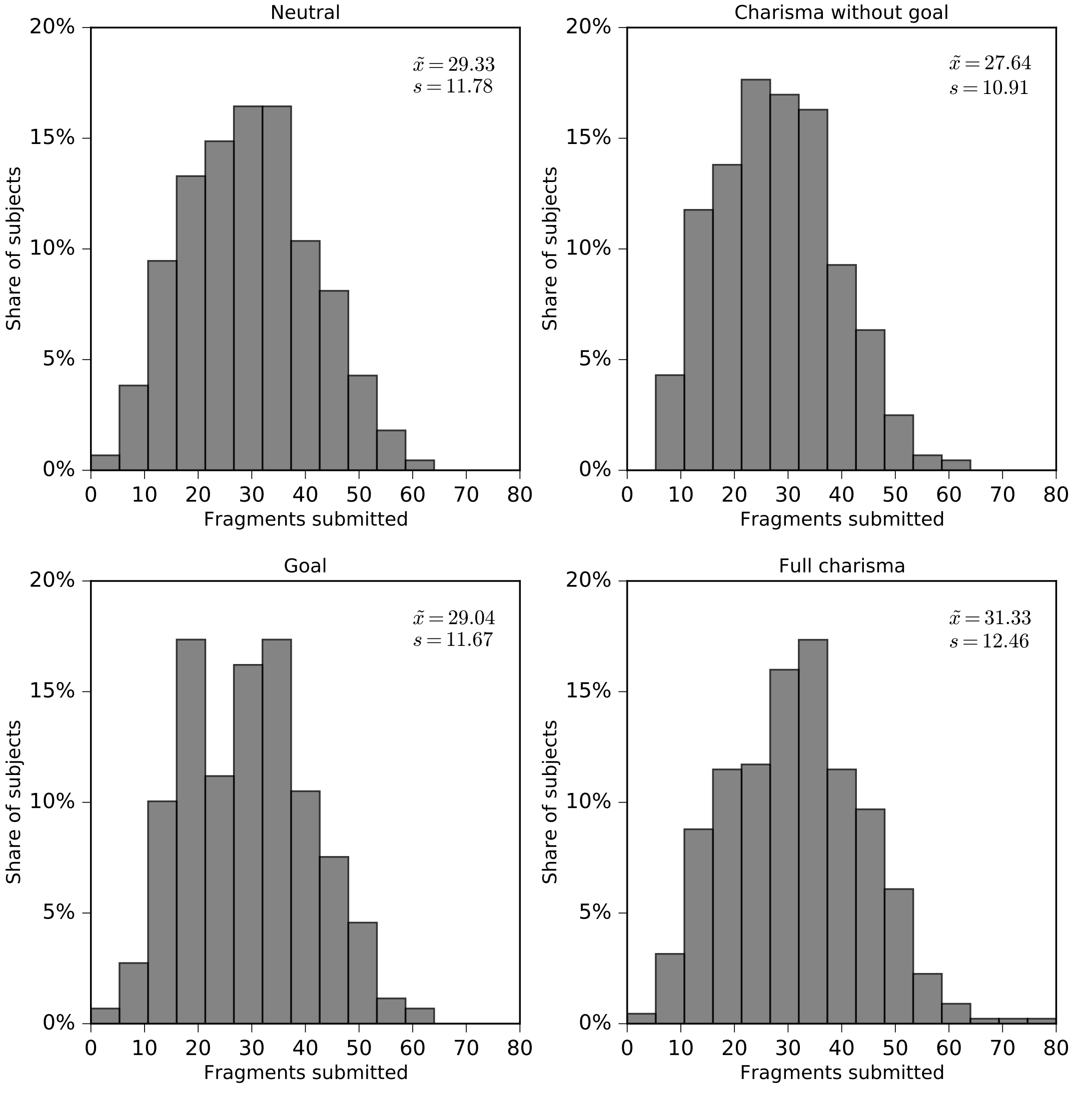
Table S12: Coding of sentences for *Neutral* and *Goal*, study 2

No.	**Treatment**	**Sentence**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**
1	Neutral & Goal	Welcome to this HIT.									
2	Neutral & Goal	Your job will be to transcribe text from historic documents from the Frick Collection and Frick Art Reference Library Archives.									
3	Neutral & Goal	You will see fragments of these documents on the screen and we kindly ask you to type the text into the blank space below the fragment using your keyboard.									
4	Neutral & Goal	We care about quantity and quality of work.									
5	Neutral & Goal	You will be paid no matter how many fragments you submit.									
6	Neutral & Goal	The transcriptions you are going to create will become searchable data points in a large database.									
7	Neutral & Goal	Your effort will help the project.						1			
8	Neutral & Goal	Each fragment you manage to transcribe will translate into one more data point.									
9	Neutral & Goal	Together with hundreds of other MTurkers working on this HIT, your work will contribute to preserve and build knowledge of past events.							1		
10	Neutral & Goal	This data can then be accessed by scholars, students or the public in general for study purposes.									
11	Neutral & Goal	We ask you to work hard and diligently as well as to produce high quality output.					1				
12	Goal	In similar HITs, MTurkers submitted roughly 25 fragments on average.								1	1
13	Goal	We ask you to aim for at least 34 fragments.								1	
14	Goal	This is a challenging goal but because you have already worked on many HITs and earned an excellent approval rate, we are confident that you will be able to meet or even exceed this goal.									1
15	Neutral & Goal	Below, you see an example of the task.									
16	Neutral & Goal	In the actual assignment, after you have submitted the text, a new fragment will appear on your screen.									
17	Neutral & Goal	In total, you will have to work on the assignment for 10 minutes.									
18	Neutral & Goal	After finishing the assignment, you will be taken to a short questionnaire.									

Table S13: Coding of sentences for *Charisma without goal* and *Full charisma*, study 2

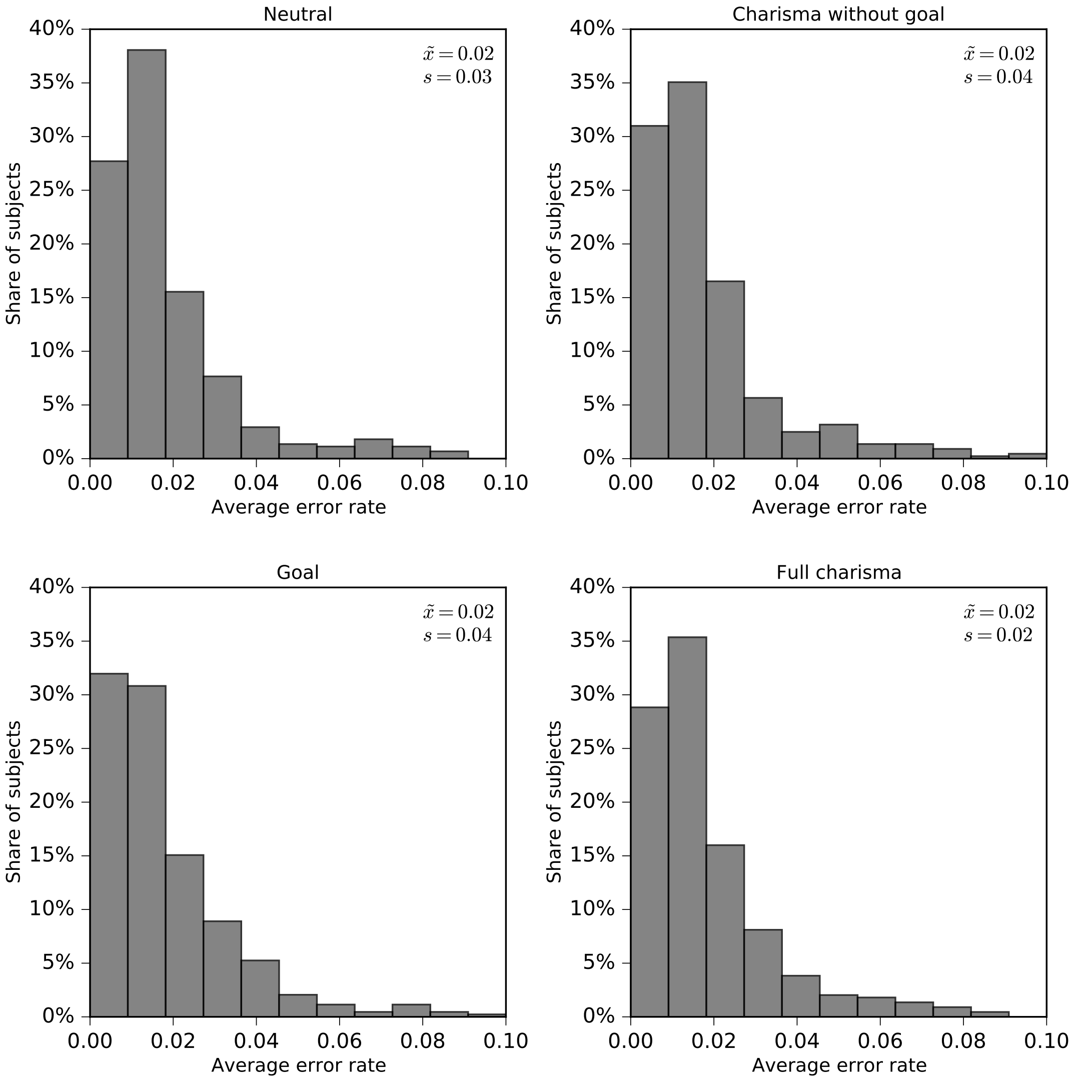
No.	**Treatment**	**Sentence**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**
1	Char. w/o Goal & Full Char.	Welcome to this HIT.									
2	Char. w/o Goal & Full Char.	Your job will be to transcribe text from historic documents from the Frick Collection and Frick Art Reference Library Archives.									
3	Char. w/o Goal & Full Char.	You will see fragments of these documents on the screen and we kindly ask you to type the text into the blank space below the fragment using your keyboard.									
4	Char. w/o Goal & Full Char.	We care about quantity and quality of work.									
5	Char. w/o Goal & Full Char.	You will be paid no matter how many fragments you submit.									
6	Char. w/o Goal & Full Char.	The transcriptions you create will become searchable data facilitating learning and research around the world.						1			
7	Char. w/o Goal & Full Char.	You might think, will my extra effort really help?		1							
8	Char. w/o Goal & Full Char.	Yes, it will!			1			1			
9	Char. w/o Goal & Full Char.	Each fragment is like a little piece of a puzzle; together with hundreds of other MTurkers, you will put the puzzle together.	1						1		
10	Char. w/o Goal & Full Char.	You can bring history to life and keep it alive.	1								
11	Char. w/o Goal & Full Char.	Just like historians, you contribute to preserve and build the public knowledge of past events.			1						
12	Char. w/o Goal & Full Char.	So, we ask you to jump in and work hard, work diligently, and produce high-quality output.					1				
13	Char. w/o Goal & Full Char.	Not only do you benefit from this job; so too will students, scholars, and the public at large.						1	1		
14	Full Char.	In similar HITs, MTurkers submitted roughly 25 fragments on average.								1	1
15	Full Char.	We ask you to aim for at least 34 fragments.								1	
16	Full Char.	This is a challenging goal but because you have already worked on many HITs and earned an excellent approval rate, we are confident that you will be able to meet or even exceed this goal.									1
17	Char. w/o Goal & Full Char.	Below, you see an example of the task.									
18	Char. w/o Goal & Full Char.	In the actual assignment, after you have submitted the text, a new fragment will appear on your screen.									
19	Char. w/o Goal & Full Char.	In total, you will have to work on the assignment for 10 minutes.									
20	Char. w/o Goal & Full Char.	After finishing the assignment, you will be taken to a short questionnaire.									

Figure S5: Histogram fragments submitted, study 2



Note: The figure shows the histogram for the number of submitted fragments in all treatments in study 2. Indicated as well are the mean ($\bar{x}$) and standard deviation (s).

Figure S6: Histogram error rate, study 2



Note: The figure shows the histogram for the average error rate per worker in all treatments in study 2. Indicated as well are the mean ($\bar{x}$) and standard deviation (s).

Table S14: Treatment effects on quantity, study 2

Model	I	II	III	IV
Dependent variable	No. Fragment	No. Fragment	No. Fragment	No. Fragment
Goal CLT	1.711***	-0.285	0.292	0.252
	(0.559)	(0.789)	(0.746)	(0.741)
Non-Goal CLT	0.296	-1.691**	-1.551**	-1.654**
	(0.559)	(0.763)	(0.731)	(0.732)
Goal CLT × Non-Goal CLT		3.983***	3.507***	3.585***
		(1.115)	(1.064)	(1.065)
Age			-0.204***	-0.202***
			(0.022)	(0.022)
Female			1.839***	1.870***
			(0.535)	(0.532)
Diverse			4.404	3.781
			(3.503)	(3.848)
Education			0.495**	0.476**
			(0.205)	(0.203)
Mobile device			-13.608***	-13.458***
			(0.924)	(0.968)
Group 2				2.686*
				(1.392)
Group 3				4.064***
				(1.394)
Group 4				6.716***
				(1.401)
Group 5				1.475
				(1.408)
Group 6				5.731***
				(1.357)
Group 7				4.994***
				(1.358)
Group 8				4.090***
				(1.362)
Group 9				4.172***
				(1.243)
Group 10				3.449***
				(1.264)
Group 11				5.348***
				(1.407)
Group 12				3.941***
				(1.371)
Group 13				3.380**
				(1.404)
Group 14				2.268*
				(1.379)
Group 15				6.714***
				(1.479)
Constant	28.335***	29.327***	34.174***	30.293***
	(0.485)	(0.559)	(1.331)	(1.569)
N	1768	1768	1768	1768
R^2	0.005	0.013	0.103	0.126
F	4.734	7.408	40.894	16.163
$P(> F)$	0.009	0.000	0.000	0.000

Note: The table reports linear regression results of the number of fragments submitted per worker on a set of explanatory variables. "Goal CLT": indicator variable taking the value of one if the treatment uses goal-related CLTs. "Non-Goal CLT": indicator variable taking the value of one if the treatment employed non-goal related CLTs. "Age": continuous variable measuring a worker's age. "Female": indicator variable taking the value one if the worker is a female. "Diverse": indicator variable taking the value one if the worker identifies as neither male nor female."Education" is an ordinally scaled variable: 1 = High School, 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; "Mobile device": indicator variable taking the value one if the worker used a mobile device. "Group X": Indicator variables for each fragment group. Robust standard errors in parentheses ($^{*} : p < 0.1$, $^{**} : p < 0.05$, $^{***} : p < 0.01$).

Table S15: Treatment effects on quality, study 2

Model	I	II	III	IV
Dependent variable:	Error rate	Error rate	Error rate	Error rate
Goal CLT	-0.000	0.001	0.001	0.001
	(0.002)	(0.003)	(0.002)	(0.002)
Non-Goal CLT	-0.001	0.001	0.001	0.001
	(0.002)	(0.003)	(0.002)	(0.002)
Goal CLT × Non-Goal CLT		-0.003	-0.003	-0.003
		(0.003)	(0.003)	(0.003)
Age			-0.000	-0.000
			(0.000)	(0.000)
Female			-0.005***	-0.005***
			(0.002)	(0.002)
Diverse			-0.005	-0.005
			(0.008)	(0.008)
Education			0.001**	0.001**
			(0.000)	(0.000)
Mobile device			0.030***	0.031***
			(0.008)	(0.008)
Group 2				-0.004
				(0.004)
Group 3				-0.008*
				(0.004)
Group 4				-0.013***
				(0.004)
Group 5				0.0000
				(0.005)
Group 6				-0.004
				(0.005)
Group 7				-0.009**
				(0.004)
Group 8				0.003
				(0.005)
Group 9				-0.001
				(0.005)
Group 10				-0.004
				(0.004)
Group 11				-0.007*
				(0.004)
Group 12				0.003
				(0.005)
Group 13				-0.004
				(0.004)
Group 14				-0.007
				(0.004)
Group 15				-0.006
				(0.0043)
Constant	0.021***	0.020***	0.019***	0.023***
	(0.002)	(0.002)	(0.004)	(0.005)
N	51868	51868	51868	51868
R^2	0.003	0.003	0.004	0.005
R^2 (Within)	0.000	0.000	0.000	0.000
R^2 (Between)	-0.000	0.000	0.047	0.067

Note: The table reports estimation results from random effects panel regressions in which the error rate per fragment and worker is regressed on a set of explanatory variables. "Goal CLT": indicator variable taking the value of one if the treatment uses goal-related CLTs. "Non-Goal CLT": indicator variable taking the value of one if the treatment employed non-goal related CLTs. "Age": continuous variable measuring a worker's age. "Female": indicator variable taking the value one if the worker is a female. "Diverse": indicator variable taking the value one if the worker identifies as neither male nor female. "Education" is an ordinally scaled variable: 1 = High School, 2 = Some College, 3 = 2 year College Degree, 4 = 4 year College Degree, 5 = Masters Degree, 6 = Doctoral Degree; "Group X": Indicator variables for each fragment group. Robust standard errors in parentheses ($^{*}: p < 0.1$, $^{**}: p < 0.05$, $^{***}: p < 0.01$).

Table S16: Quality vs. quantity, study 2

Model	I	II	III	IV
Dependent variable:	Avg. error rate	Avg. error rate	Avg. error rate	Avg. error rate
Share fragments	-0.092***	-0.093***	-0.100***	-0.121***
	(0.010)	(0.010)	(0.010)	(0.031)
Constant	0.046***	0.045***	0.046***	0.052***
	(0.003)	(0.004)	(0.003)	(0.010)
Intercepts	No	Yes	No	Yes
Slopes	No	No	Yes	Yes
N	1768	1768	1768	1768
R^2	0.094	0.094	0.095	0.098
F	86.563	28.988	23.942	17.972
$P(> F)$	0.000	0.000	0.000	0.000

Note: The table reports estimation results for regressions in which the time averaged error rate per worker is regressed against the number of submitted fragments per worker as a percentage of the total number of fragments a worker could submit ("Share fragments"). Indicated as well is whether the model specification includes indicator variables for each treatment ("Intercepts") and treatment specific slopes ("Slopes") (estimate results not reported here). Robust standard error in parentheses (* : $p < 0.1$, ** : $p < 0.05$, *** : $p < 0.01$).

6.2 Instructions study 1

You will be paid a **fixed compensation of $2** for working on this project. [Piece rate treatments: In addition, you will receive **a bonus of $0.01 ($0.05)** for each completed fragment.] The compensation will be sent to you within two days after the completion of this HIT.

[Approval treatments: Once you have completed the HIT, you will be approved automatically, which means that your performance will **not affect your approval rate**.][28]

[Clarification treatments: In order to pay the bonus in due time, we pay it for submitted fragments without controlling for typing errors. Once you have completed the HIT, you will be approved automatically, which means that your performance will **not affect your approval rate**.][29]

{NEW PAGE}

Please read the instructions below carefully. In the assignment you will be shown fragments of an ancient Latin text. You are asked to type the text into the blank space below the fragment using your keyboard. If you can't read a specific letter, please insert a question mark instead of the letter.

Below, you see an example of the task. In the actual assignment, after you have submitted the text, a new fragment will appear on your screen. In total, you will have to work on the assignment for 10 minutes. We ask you to complete as many fragments as possible.

After finishing the assignment, you will be taken to a short questionnaire.

[EXAMPLE FRAGMENT HERE]

{NEW PAGE FOR PRAISE TREATMENTS}

[Praise treatments: Before you start, we want to emphasize how happy we are that you've decided to work for us. You've proven to be a successful and diligent worker on MTurk with an impressive approval rate!]

{NEW PAGE FOR REFERENCE POINT TREATMENTS}

[Reference point treatments: Efficient work is important. Please try to submit at least 25 fragments.]

[28] These treatments where pooled with the main treatments, compare footnote 3.

[29] We discuss these treatments in Section 3.3.3.

6.3 Instructions study 2

You will be paid a **fixed compensation of $3** for working on this project. The compensation will be sent to you within two days after the completion of this HIT.

{New page}

Neutral treatment
Welcome to this HIT. Your job will be to transcribe text from historic documents from the Frick Collection and Frick Art Reference Library Archives. You will see fragments of these documents on the screen and we kindly ask you to type the text into the blank space below the fragment using your keyboard. We care about quantity and quality of work. You will be paid no matter how many fragments you submit.

The transcriptions you are going to create will become searchable data points in a large database. Your effort will help the project. Each fragment you manage to transcribe will translate into one more data point. Together with hundreds of other MTurkers working on this HIT, your work will contribute to preserve and build knowledge of past events. This data can then be accessed by scholars, students or the public in general for study purposes. We ask you to work hard and diligently as well as to produce high quality output.

Below, you see an example of the task. In the actual assignment, after you have submitted the text, a new fragment will appear on your screen. In total, you will have to work on the assignment for 10 minutes. After finishing the assignment, you will be taken to a short questionnaire.

Goal Treatment (same as *Neutral* plus paragraph for goals)
Welcome to this HIT. Your job will be to transcribe text from historic documents from the Frick Collection and Frick Art Reference Library Archives. You will see fragments of these documents on the screen and we kindly ask you to type the text into the blank space below the fragment using your keyboard. We care about quantity and quality of work. You will be paid no matter how many fragments you submit.

The transcriptions you are going to create will become searchable data points in a large database. Your effort will help the project. Each fragment you manage to transcribe will translate into one more data point. Together with hundreds of other MTurkers working on this HIT, your work will contribute to preserve and build knowledge of past events. This data can then be accessed by scholars, students or the public in general for study purposes. We ask you to work hard and diligently as well as to produce high quality output.

In similar HITs, MTurkers submitted roughly 25 fragments on average. We ask you to aim for at least 34 fragments. This is a challenging goal but because you have already worked on many HITs and earned an excellent approval rate, we are confident that you will be able to meet or even exceed this goal.

Below, you see an example of the task. In the actual assignment, after you have submitted the text, a new fragment will appear on your screen. In total, you will have to work on the assignment for 10 minutes. After finishing the assignment, you will be taken to a short questionnaire.

Charisma without goal treatment
Welcome to this HIT. Your job will be to transcribe text from historic documents from the Frick Collection and Frick Art Reference Library Archives. You will see fragments of these documents on the screen and we kindly ask you to type the text into the blank space below the fragment using your keyboard. We care about quantity and quality of work. You will be paid no matter how many fragments you submit.

The transcriptions you create will become searchable data facilitating learning and research around the world. You might think, will my extra effort really help? Yes, it will! Each fragment is like a little piece of a puzzle; together with hundreds of other MTurkers, you will put the puzzle together. You can bring history to life and keep it alive. Just like historians, you contribute to preserve and build the public knowledge of past events. So, we ask you to jump in and work hard, work diligently, and produce high-quality output. Not only do you benefit from this job; so too will students, scholars, and the public at large.

Below, you see an example of the task. In the actual assignment, after you have submitted the text, a new fragment will appear on your screen. In total, you will have to work on the assignment for 10 minutes. After finishing the assignment, you will be taken to a short questionnaire.

Full charisma treatment (same as *Charisma without goal* plus paragraph for goals from *Goal* treatment)
Welcome to this HIT. Your job will be to transcribe text from historic documents from the Frick Collection and Frick Art Reference Library Archives. You will see fragments of these documents on the screen and we kindly ask you to type the text into the blank space below the fragment using your keyboard. We care about quantity and quality of work. You will be paid no matter how many

fragments you submit.

The transcriptions you create will become searchable data facilitating learning and research around the world. You might think, will my extra effort really help? Yes, it will! Each fragment is like a little piece of a puzzle; together with hundreds of other MTurkers, you will put the puzzle together. You can bring history to life and keep it alive. Just like historians, you contribute to preserve and build the public knowledge of past events. So, we ask you to jump in and work hard, work diligently, and produce high-quality output. Not only do you benefit from this job; so too will students, scholars, and the public at large.

In similar HITs, MTurkers submitted roughly 25 fragments on average. We ask you to aim for at least 34 fragments. This is a challenging goal but because you have already worked on many HITs and earned an excellent approval rate, we are confident that you will be able to meet or even exceed this goal.

Below, you see an example of the task. In the actual assignment, after you have submitted the text, a new fragment will appear on your screen. In total, you will have to work on the assignment for 10 minutes. After finishing the assignment, you will be taken to a short questionnaire.